# Primary Level Classification of Brain Tumor using PCA and PNN

Dr. Mrs. K.V.Kulhalli

Department of Information Technology, D.Y.Patil Coll. of Engg. And Tech. Kolhapur,Maharashtra,India kvkulhalli@gmail.com Mrs.V. S. Kolge Departement of Electonics and Telecommunication, D.Y.Patil Coll. of Engg. And Tech Kolhapur,Maharashtra,India *kolge.varada@gmail.com* 

*Abstract*— Probabilistic neural networks (PNN) are finding many uses in the medical diagnosis application. The goal of this paper is to use Probabilistic Neural Network (PNN) with one important mathematical technique 'Principal Component Analysis' (PCA) for preliminary level brain tumor classification. As a result, the tested Magnetic Resonance Image (MRI) of brain is classified either ','benign' or malignant. Automated classification of brain tumors is performed in two stages. Feature extraction using Principal Component Analysis (PCA) and classification using Probabilistic Neural Network (PNN).

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Keywords- Principal Component Analysis, Probabilistic Neural Network, Magnetic Resonance Image

## I. INTRODUCTION

PNN provides a powerful tool to help doctors to analyze, model and make sense of complex clinical data across a broad range of medical applications. Most applications of PNN in medical field are classification problems; that is, the task is on the basis of the measured features to assign the patient to one of a small set of classes of particular disease.

Conventional methods of monitoring and diagnosing the diseases rely on detecting the presence of particular features by a human observer. Due to large number of patients in intensive care units and the need for continuous observation of such conditions, several techniques for automated diagnostic systems have been developed in recent years to attempt to solve this problem. Such techniques work by transforming the mostly qualitative diagnostic criteria into a more objective quantitative feature classification problem.

PNN are finding many uses in the medical diagnostic application. According to Qeethara Kadhim Al-Shayea [1].PNN provide a powerful tool to help doctors to analyze, model and make sense of complex clinical data across a broad range of medical applications. Most of the applications provide the solution to the classification problem. According to N. Kwak, and C. H. Choi [2] Feature selection plays an important role in classifying systems such as PNN.The higher performance with lower computational effort is expected with this process. One of the most popular methods for dealing with this problem is the PCA method. This method transforms the existing attributes into new ones considered to be crucial. E. D. Ubeyli and I. Guler [3] used feature extraction methods in automated diagnosis of arterial diseases. Since classification is more accurate when the pattern is simplified through representation by important features, feature extraction and selection play an important role in classifying systems.

T.Logeswari, and M. Karnan [5] used image segmentation based on the soft computing for improved implementation of the brain tumor detection. The MRI brain image is acquired from patient's database and then Image acquisition, preprocessing, image segmentation is performed for brain tumor detection. Georgiadis, et.al [6] also did the work for improving brain tumor characterization on MRI by probabilistic neural network and non-linear transformation of textural features. According to Chettri, S. R. and Cromp, R.F., the PNN architecture can be used for high speed classification of remotely sensed imagery and can be applied to remotely sensed data

# II. RESEARCH METHOD

The automated classification of brain MRI images by using some prior knowledge like pixel intensity and some anatomical features are proposed [7]. Currently there are no methods widely accepted, therefore automatic and reliable methods for tumor detection are of great need and interest. The application of PNN in the classification of data for MRI images problems are not fully utilized yet. These include the clustering and classification techniques especially for MRI images problems with huge scale of data and consuming time and energy if done manually. Thus, fully understanding the recognition, classification or clustering techniques is essential to the developments of Neural Network systems particularly in medicine problems. Decision making will be performed in two stages:

- 1. Feature extraction using the PCA and
- 2. Classification using PNN.

The performance of the PNN classifier will be evaluated in terms of training performance and classification accuracies. PNN gives fast and accurate classification and will be a promising tool for classification of the tumors. Following Fig 1 shows block diagram of the proposed system.

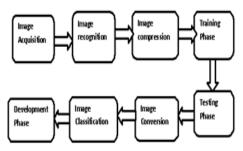


Figure 1. Block Diagram of the presented work

**Image Acquisition**: - Maximum MRI Images of brain are collected form possible resources like Radiologists, Internet, Medical Atlases and cancer Hospitals.

**Image recognition and Image compression:** - The Database of MRI images is prepared. All the images are converted into one standard size. The colour images are converted into gray image for simplicity. Also the images are converted into 2-D or 1-D according to the requirement.

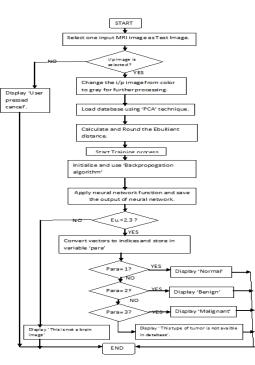
**Training Phase:** - A Mathematical technique 'PCA' is used to extract feature vectors of all images in the database. Back Propagation algorithm is used to train the neural network.

**Testing Phase**: - Feature vector of the test image is computed in this phase. Euclidean Distance is also calculated to decide in which class of the input image is to be fitted.

**Image Conversion:** - MR images are converted into matrices form using MATLAB as a tool.

**Image Classification**: - The Feed Forward PNN is used to classify MRI images.

**Development Phase:** - Performance analysis based on the result is carried out in the development phase.



III. IMPLEMENTATION

Figure 2. Flow chart of the presented system.

In order to implement the proposed system, Matlab is used as a tool. mri images of brain are stored in the database. The Flow chart of the Presented system is shown in fig.

### IV. EXPERIMENTATION AND RESULT

### **Database details**

The presented work is implemented using MRI images of brain of patients suffering from brain disorders. The dataset considered here is of two types the first type, is the same types of MRI images ('T2 weighted flair') images of brain are used and in second type is different types, where T1 weighed and T2 weighed images of brain are used for training purpose. These databases contain total of 90 MRI images of which 30 are Normal, 30 are Benign and 30 are Malignant already attested by experts. For testing purpose, total 38 images are used. Out of which13 are Benign, 13 are Malignant and 12 are absolutely Normal. All the images used for training and testing purpose are of various sizes and various dimensions like 256 x 256 or 128 x 128 or 204 x 256. These images are collected from Radiologist, Hospitals and some from cancer diagnosis centers website.

### **Classifier results**

Once dataset is collected, it follows various steps of presented system described in earlier section. The Snapshots of designed system is illustrated in following figures. The Four buttons are created using GUI i.e. Browse, Load Database, Training, Classification.

1) Two blank boxes are created to display the images.

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1	[] funct	ion varargout = gui (varargin)	Probabiliatic Neural Network For Brain Tumor Classification	
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3		GUI, by itself, creates a		
4		singleton*.		
5				
6		H = GUI returns the handle		
9		the existing singleton*.		
8				
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0	4	*See GUI Options on GUIDE .	Classification	Clear
9		instance to run (singleton)		

Fig.3 Initial display of GUI

2) Some collected MRI images used as database are as follows.

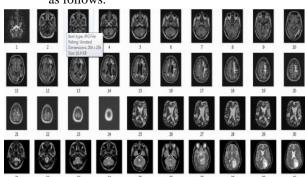


Fig.4 Sample images used in Database

 Function of 'Browse' – Select one of the MRI image for testing (input image)

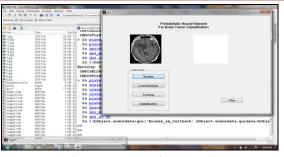


Fig.5 Function of 'Browse'

Input image is immediately converted into Gray Image for further processing.

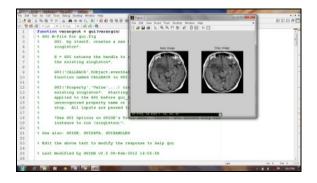


Fig. 6 Input image is converted into gray image

4) Function of 'Load Database' – Database is loaded successfully using 'Principal Component Analysis Technique.'

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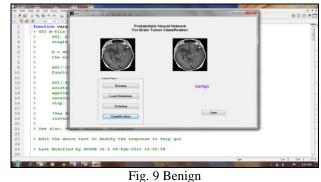
Fig.7 Function of 'Load database'

4) Neural network is trained using Back propagation algorithm.



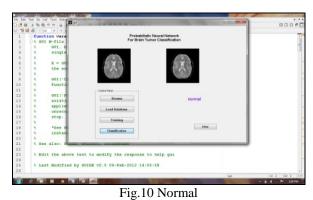
Fig.8 Function of 'Training

### 5) Results of classification.





a)



b) Malignant

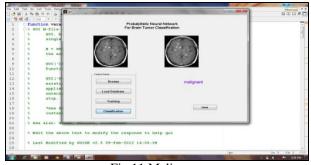


Fig.11 Malignant

### Performance measures

A. True Positive (TP), Sick people correctly diagnosed as sick, correctly identified

B. True Negative (TN), Healthy people correctly identified as healthy, incorrectly identified.

C. False Positive (FP), Healthy people incorrectly identified as sick, correctly rejected.

D. False Negative (FN), incorrectly identified Sick people incorrectly identified as healthy, incorrectly rejected.

Using same types of images in database for training purpose, classifier results are as follows.

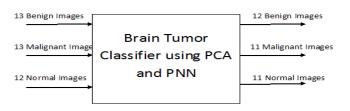


Fig.12 Classifier results for database using same type of images

The test result of each image and corresponding

performance measures can be represented in tabular format as below .

<u>Şr</u> no	Image	Actual	Result of	Performance
	Name	type	the	measure
			system	
1	DB1	Benign	Benign	TP
2	DB2	Benign	Benign	TP
3	DB3	Benign	Benign	TP
4	DB4	Benign	Benign	TP
5	DB5	Benign	Benign	TP
6	DB6	Benign	Benign	TP
7	DB7	Benign	Benign	TP
8	DB8	Benign	Benign	TP
9	DB9	Benign	Benign	TP
10	DB10	Benign	Benign	TP
11	TB1	Benign	Unable to	FN
			classify	
12	TB2	Benign	Benign	TP
13	TB3	Benign	Benign	TP
14	DM1	Malignant	Malignant	TP
15	DM2	Malignant	Malignant	TP
16	DM3	Malignant	Malignant	TP
17	DM4	Malignant	Malignant	TP
18	DM5	Malignant	Malignant	TP
19	DM6	Malignant	Malignant	TP
20	DM7	Malignant	Malignant	TP

<u>Sr</u> no	Image	Actual	Result of	Performance
	Name	type	the	measure
			system	
21	DM8	Malignant	Malignant	TP
22	DM9	Malignant	Malignant	TP
23	DM10	Malignant	Malignant	TP
24	DM11	Malignant	Malignant	TP
25	TM2	Malignant	Benign	FN
26	TM3	Malignant	Benign	FN
27	DN1	Normal	Normal	TN
28	DN2	Normal	Normal	TN
29	DN3	Normal	Normal	TN
30	DN4	Normal	Normal	TN
31	DN5	Normal	Normal	TN
32	DN6	Normal	Normal	TN
33	DN7	Normal	Normal	TN
34	DN8	Normal	Normal	TN
35	DN9	Normal	Normal	TN
36	DN10	Normal	Normal	TN
37	TN1	Normal	Benign	FP
38	TN2	Normal	Normal	TN

### Table 1.1

# The Total no of TP, TN, FP, FN using same types of images in database are as follows

$\oplus$				
	RESULTS	S USING SAME TYP	E S OF IMAGES IN DA	ATABASE
	TOTAL TP	TOTAL TN	TOTAL FP	TOTAL FN
	23	11	1	3

Table 1.2

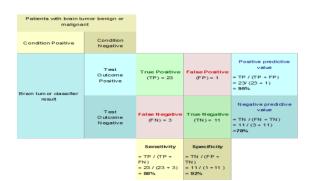


Fig. 13 Results at a glance for database using same type of images

Using different types of images in database for training purpose, classifier results are as follows.

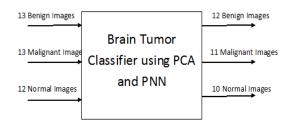


Fig.14 Classifier results for database using different types of images

The test result of each image and corresponding performance measure can be represented in tabular format as below.

Sr no	Image	Actual	Result of the	Performance
	Name	type	system	measure
1	DB1	Benign	Benign	TP
2	DB2	Benign	Benign	TP
3	DB3	Benign	Benign	TP
4	DB4	Benign	Benign	TP
5	DB5	Benign	Benign	TP
6	DB6	Benign	Benign	TP
7	DB7	Benign	Benign	TP
8	DB8	Benign	Benign	TP
9	DB9	Benign	Benign	TP
10	DB10	Benign	Benign	TP
11	TB1	Benign	Unable to	FN
			classify	
12	TB2	Benign	Benign	TP
13	TB3	Benign	Benign	TP
14	DM1	Malignant	Malignant	TP
15	DM2	Malignant	Malignant	TP
16	DM3	Malignant	Malignant	TP
17	DM4	Malignant	Malignant	TP
18	DM5	Malignant	Malignant	TP
19	DM6	Malignant	Malignant	TP
20	DM7	Malignant	Malignant	TP

<u>Sr</u> no	Image	Actual	Result of the	Performance
	Name	type	system	measure
21	DM8	Malignant	Malignant	TP
22	DM9	Malignant	Malignant	TP
23	DM10	Malignant	Malignant	TP
24	DM11	Malignant	Malignant	TP
25	TM2	Malignant	Benign	FN
26	TM3	Malignant	Benign	FN
27	DN1	Normal	Normal	TN
28	DN2	Normal	Normal	TN
29	DN3	Normal	Normal	TN
30	DN4	Normal	Normal	TN
31	DN5	Normal	Normal	TN
32	DN6	Normal	Normal	TN
33	DN7	Normal	Normal	TN
34	DN8	Normal	Normal	TN
35	DN9	Normal	Normal	TN
36	DN10	Normal	Normal	TN
37	TN1	Normal	Benign	FP
38	TN1	Normal	Benign	FP

Table 1.3

The Total TP, TN, FP, FN using same type of images in database is as follows

RESULTS USING DIFFERENT TYPES OF IMAGES IN DATABASE					
TOTAL TP TOTAL TN TOTAL FP TOTAL FN					
23	10	2	3		

Table 1.4

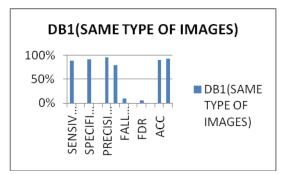
Patients with brain tu maligna				
Condition Positive Condition Negative				
Brain tum or classifier	Test Outcome Positive	True Positive (TP) = 23	False Positive (FP) = 2	Positive predictive value = TP / (TP + FP) = 23/ (23 + 2) = 92%
result	Test Outcome Negative	False Negative (FN) = 3	True Negative (TN) = 10	Negative predictiv value = TN / (FN + TN) = 10 / (3 + 10) =76.92%
		Sensitivity = TP / (TP + FN) = 23 / (23 + 3) = 88%	Specificity = TN / (FP + TN) = 10 / (2 + 10 ) = 83%	

Fig.15 Results at a glance for database using different types of images

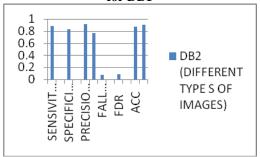
The statistical measures for the two types of database can be calculated using following formulas and can be represented in Table 7.6.

Sr.	Performance measure	Formula	For	For Different
No.			Same	type of images
			type of	in database
			images	
			in	
			database	
1	sensitivity or true positive rate	= TP / P	88%	88%
	(TPR)	= TP / (TP		
		+ FN)		
2	Specificity (SPC) or True	= TN / N	91%	83%
	Negative Rate	=TN/ (FP +		
		TN)		
3	Precision or positive predictive	= TP / (TP	95%	92%
	value (PPV)	+ FP )		
4	negative predictive value (NPV)	= TN /( TN	79%	77%
		+ FN)		
5	fall-out or false positive rate	= FP / N	9%	7%
	(FPR)	= (1 - SPC)		
6	False discovery rate (FDR)	= FP / (TP	5%	8%
		+ FP )		
		=(1-PPV)		
7	Accuracy (ACC)	= (TP+ TN)	89%	87%
		/(TP + TN		
		+ FP + FN		
		)		
8	F1 score is the harmonic	=2TP/ (2TP	92%	90%
	mean of precision and sensitivity	+FP+FN)		

Table 1.4



# Fig.16 Graphical representation of statistical measures for DB1



# Fig. 17Graphical representation of statistical measures for DB1

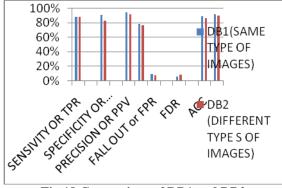


Fig.18 Comparison of DB1 and DB2

### V. CONCLUSION AND FUTURE SCOPE

From the above results of various performance measures we can conclude that the accuracy and specificity increases for the database using same type of MRI image of human brain. The accuracy of the classifier can be further increased if number of images used in database is increased. PNNs have a lot to offer to modern medicine. At the moment they are mainly used for pattern recognition using images but experiments are being done in using PNNs to model parts of the human body. Neural networks will never replace human experts but they can help in screening and can be used by experts to double-check their diagnosis.

Medicine has always benefited from the forefront of technology. Technology advances like computers, lasers, ultrasonic imaging, etc. have boosted medicine to extraordinary levels of achievement. PNN is currently the next promising area of interest. It is believed that neural networks will have extensive application to biomedical problems in the next few years. Already, it has been successfully applied to various areas of medicine, such as diagnostic systems, biochemical analysis, image analysis, and drug development.

### **Diagnostic Systems**

PNNs are extensively used in diagnostic systems. They are normally used to detect cancer and heart problems. The benefits of using PNNs are that they are not affected by factors such as fatigue, working conditions and emotional state.

#### **Biochemical Analysis**

PNNs are used in a wide variety of analytical chemistry applications. In medicine, ANNs have been used to analyse blood and urine samples, track glucose levels in diabetics, determine ion levels in body fluids, and detect pathological conditions such as tuberculosis.

#### Image

Analysis

PNNs are used in the analysis of medical images from a variety of imaging modalities. Applications in this area include tumour detection in ultra-sonograms, classification of chest x-rays, tissue and vessel classification in magnetic resonance images (MRI), determination of skeletal age from x-ray images, and determination of brain maturation.

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