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MRI Brain Images-A Relative Study Between HGNN And IPSONN

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Abstract— Image processing involves the management of images to remove information to highlight or suppress certain phases of the information, contained in the image or perform image analysis to extract hidden information. The recent imaging modalities in medicine, such as Magnetic Resonance Imaging (MRI) generate images directly in digital form. Estimation of the size of the whole organ, portions of the organ and/or objects surrounded by an organ i.e. tumors is clinically important in the analysis of medical image. The relative change in size, shape and the spatial relations among anatomical structures attained from intensity scatterings offer important data in clinical diagnosis for monitoring disease progression for the radiologist. Imprecise, computer algorithms for the description of anatomical structures and other regions of interest play a vital role in numerous biomedical imaging applications. There is no single algorithm which provides the best effects for segmentation of every medical image. Every imaging classification has its own open limits. Here it is primarily focused on Hybrid Genetic Algorithm- Neural Network (HGNN) and Improved PSO Neural Network (IPSONN) and a concise comparison between these two.

Keywords:- *Biomedical imaging, HGNN, IPSONN, MRI, Neural Network.*

I. INTRODUCTION

A digital image is simply a matrix where each number represents the brightness at regularly spaced points or very small regions in the image. Image acquisition involves capturing the images in the suitable form. Preprocessing improves the quality of the data by reducing artefact. Segmentation groups pixel into regions, hereby defining the boundaries of the region of interest. Feature extraction and selection provides the measurement vectors. Feature extraction is followed by presentation or classification and is performed by estimating different features of the segmented region. Figure 1 shows the generic block diagram of Image analysis system.

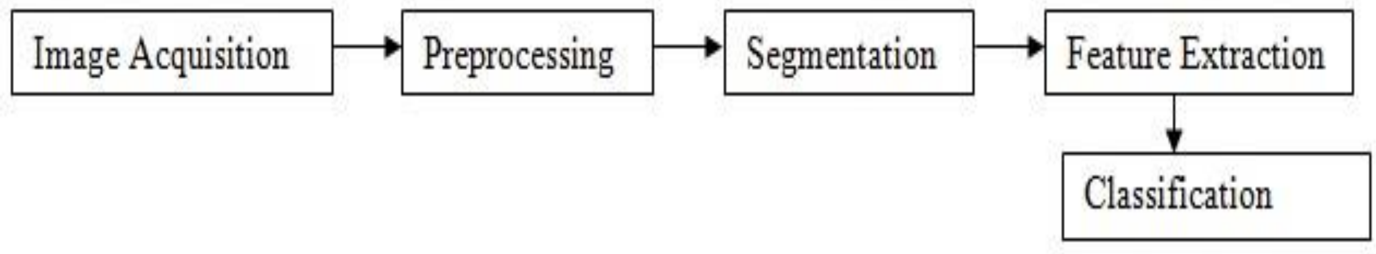

Figure 1: shows the generic block diagram of Image analysis system

II. RELATIVE STUDY

A. Hybrid Genetic Algorithm Neural Networks (HGNN)

This methodology is divided into four steps.

- Pre-processing
- Feature Extraction
- Feature selection using HGA
- Tissue Classification by Neural Networks

1) Pre-processing

The image preprocessing includes three steps namely, Histogram equalization-a system that spreads out intensity values above the whole scale to obtain uniform histogram that enhances the contrast of an image, Binarization-which converts gray scale image into a binary image based on some threshold value and Morphological operations-sharpen regions and fill gaps of binarized image.

2) Feature Extraction

The feature extraction includes separation of normal brain tissues from abnormal brain tissues. In this case Gray Level Co-occurrence Matrix is used to separate the tissues.

3) Feature selection using HGA

The following features like Contrast, Angular Second Moment, Homogeneity, Inverse Difference Moment, energy, Entropy, Variance are selected by genetic algorithm.

4) Tissue Classification by Neural Networks

The classification of brain images into White Matter (WM),Gray Matter (GM),Cerebro spinal fluid(CSF), edema and tumour using neural networks converts the input into a set of target categories. The neural network is used to select data, create and train a network and evaluate its performance. A feed forward network is used to classify vectors arbitrarily well. The network is trained using back propagation. The input and target is entered into the network and the error is corrected. Training phase stops automatically when the generalization stops improving [11].

B. Improved Particle Swarm Optimization and Neural Networks(IPSONN)

As the name implies, IPSO has an improved performance than the swarm optimization technique. Here IPSO is merged with Feed Forward Back Propagation(FFBNN).A feed forward neural network is an artificial network in which the information moved only in one direction and no more cycles are formed. A feed forward back propagation algorithm works in two steps;1)values are feed forwarded,2)error calculation and sending it back to the previous layers. The IPSO includes four stages namely

- Segmentation
- Extraction of features
- Feature selection by IPSO
- Classification using FFBNN

1) Tissue Segmentation

The tissue segmentation includes Normal Tissue Segmentation and Abnormal Tissue Segmentation. Before the segmentation process, the input images are subjected to preprocessing, where the skull stripping method is applied to the input images to remove the dark rings surrounding the brain tissues [12].During Normal Tissue Segmentation, the normal brain tissues like White Matter (WM),Gray Matter(GM),and Cerebro Spinal Fluid(CSF) are segmented. The abnormal tissue classification includes histogram based, thresholding function and region growing method to separate the abnormal tissues like edema and tumors.

2) Feature Extraction

During feature analysis training patterns are generated from the MRI images. Seven features are extracted from the segmented images. Among these seven features, two features are histogram based, two are from statistical and the remaining three from the wavelet. The mean value for all features extracted from the non-zero blocks is computed.

3) Heuristic feature selection by IPSO

The feature selection process by IPSO method includes (i)initialization, where the particles are generated. (ii) Parameters-the position of particle, its velocity, the learning parameters, own inertia, weight, and utmost amount of iterations are defined. (iii) Fitness (iv) Updating the velocity and position. (v) Stopping criteria, where the final optimal feature from the IPSO is exploited.

4) Tissue Classification by FFBNN

The feature set is given to the FFBNN classifier for training process and this classifier is represented as c-FFBNN.

Step1: Assign input weights to neurons
Step2: Calculate the learning error for the neural network [12].
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III. RELATIVE ANALYSIS

The classification performance of IPSONN and HGNN are analyzed. HGNN utilized hybrid genetic approach and IPSONN utilized swarm optimization technique. This classification method result of IPSONN is shown in Table 1 and that of HGNN is shown in Table2.The graphical representation of the average performance of IPSONN and HGNN are shown in figures 2 a, b, c.

Table1: Performance of IPSONN method in classifying WM, GM, CSF, edema, tumor.

IPSONN	WM	GM	CSF	edema	tumor
TP	1	1	1	1	0
FP	0	1	0	0	1
TN	4	3	4	4	4
FN	0	0	0	0	0
Sensitivity	100	100	100	100	0
FPR	0.0	25.0	0.0	0.0	20.0
ACC	100	80	100	100	80
Specificity	100	75	100	100	80
PPV	100	50	100	100	0
NPV	100	100	100	100	100
FDR	0	50	0	0	100
MCC	44.7	43.3	44.7	44.7	0

A graphical representation of the average performance in tissue classification [11], [12] is shown below. Figure 2 a, b, c. shows comparative results of the graphical representation of WM, GM,CSF, tumor, and edema tissue classification performance for IPSONN and HGNN methods. When IPSONN and HGNN are compared with each other, IPSONN has higher accuracy in GM, edema rather than HGNN. But the other two tissues have same accuracy results for both IPSONN and HGNN. The overall mean accuracy of IPSONN is 95%, while that of HGNN is 91%.

Table2:Performance of HGNN method in classifying WM, GM, CSF, edema, tumor

HGNN	WM	GM	CSF	Edema	tumor
TP	1	1	1	1	1
FP	0	1	0	1	0
TN	4	3	4	3	3
FN	0	0	0	0	0
Sensitivity	100	100	100	100	50
FPR	0.0	25.0	0.0	25.0	0.0
ACC	100	80	100	80	80
Specificity	100	75	100	75	100
PPV	100	50	100	50	100
NPV	100	100	100	100	75
FDR	0	50	0	50	0
MCC	44.7	43.3	44.7	43.3	30.6

Figures 2 a, b shows that HGNN has high specificity and sensitivity in tissue classification but for the other tissues IPSONN maintains high and same sensitivity and specificity levels than the HGNN. In the case of sensitivity performance review, IPSONN and HGNN attain 87% while in the case of specificity measure IPSONN and HGNN achieve 94% and 92% resp. Hence IPSONN has higher performance in tissue classification than the HGNN [11, 12].

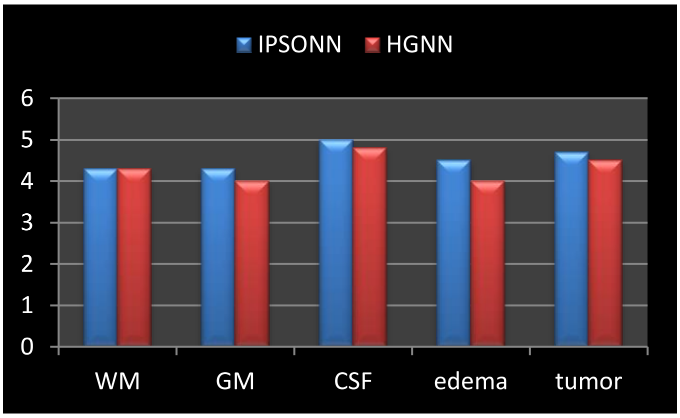

Figure 2(a): Tissue Classification result-Accuracy

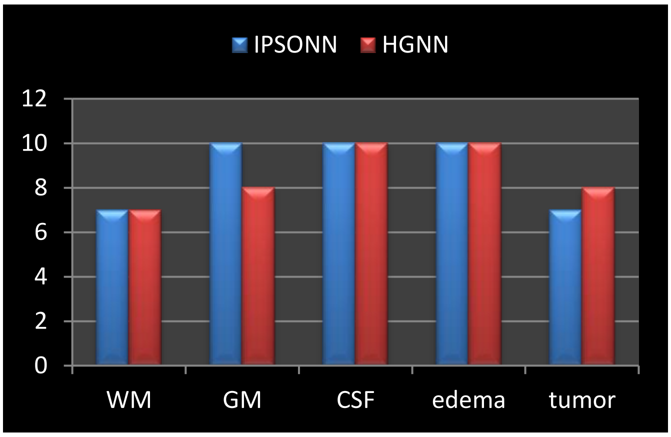

Figure 2(b): Tissue classification result-Sensitivity

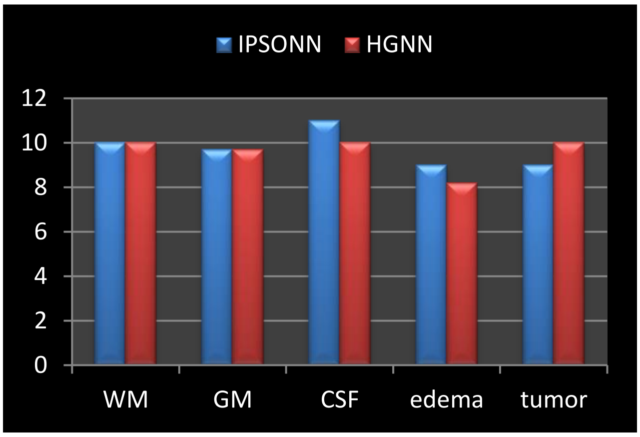

Figure 2(c):Tissue classification result-Specificity

IV. CONCLUSION

In this paper, we did a comparative study on classification method called HGNN and IPSONN to classify the normal and abnormal tissues from the MRI images. MRI brain images were utilized to analyze the results of the HGNN and IPSONN classification method. The performance analysis proved that the IPSONN method offers an average of 95%, 87%, 94% for accuracy, sensitivity and specificity measures, respectively [12]. Thus, the results show that the IPSONN achieved more classification performance than the HGNN method.

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