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Segmentation of brain MRI –A tri level PSO based approach

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Abstract— ***Brain MRI plays a very important role for radiologists to diagnose and treat various brain diseases. One of the most important applications of graph partitioning is image segmentation. Various graph based methods for image segmentation application was developed, but it produces unbalance parts and NP Complete. To address such limitations, we have investigated and developed swarm intelligence based approach in which a Tri Level Particle Swarm Optimization (TLPSO) can be applied for partitioning the graph, obtained from an image to be segmented. The proposed classification method includes three stages namely conversion, implementation, selection and extraction. To check the performance of this proposed algorithm, we carried out quantitative as well as qualitative evaluation. Segmentation by graph partitioning in which PSO technology is combined with three levels helps to reduce partitioning imbalance and considers local as well as global features for segmentation. This method generates better segmentation quality and time of convergence is reduced by considerable extent.***

Keywords— graph partitioning, MRI, neural networks, PSO

1. Introduction

MRI is the most commonly used imaging method in neuroscience and neurosurgery. MRI generates a 3D image which perfectly pictures anatomic structures of the brain. The benefits of MRI over other diagnostic imaging techniques are its higher resolution and its improved refinement of soft tissue. Separation of brain tissue in MRI is a vital pace in several medical investigation and clinical applications, involving dimension of tissue size, picturing, and examination of anatomical structures, functional brain drawing, pathology identification, surgical preparation and direction-finding, and brain structure separation. The examinations of medical imaginings for computer-aided analysis and management frequently require segmentation as an early stage. Medical image segmentation is a tough and interesting task mostly due to the unclear nature of the images It is well-known that the brain has a complex structure; thus, precise segmentation of brain is very critical for spotting tumors, edema, necrotic tissues, white matter, graymatter, cerebrospinal fluid (CSF), or vasculature in order to offer appropriate cure. A method to slice tissues into these groups is a dynamic stage in quantitative morphology of brain since most brain configurations are defined by limitations of these tissue classes [1].

MRI machines use magnetic and radio waves to look inside the body. It provides an unparalleled view inside the human body. The level of detail we can see is extraordinary compared with other imaging modality. The basic idea of MRI is to calculate the signal changes of proton caused by a strong external magnetic field and low energy radio frequency signal. In MRI only the proton in the hydrogen interact with the magnetic field. This movement makes the proton like a tiny magnet; therefore it aligns to the direction of the magnetic field in a high external static magnet [2].

Besides, manual recognition and investigation of abrasions from MR brain images are usually slow and costly and can yield unsatisfactorily high intra and inter observer variability. The effectiveness of segmented MR images in the medical investigative process depends on the blend of two, often contradictory, necessities, that is, the elimination of extra information present in the original MR images and the preservation of major information in the subsequent segmented images. MRimage segmentation approaches are often analyzed in terms of their potentiality to separate (i) Between cerebrospinal fluid (CSF), white matter, and gray matter (ii) Between normal tissues and abnormalities. In recent times; several methods have been proposed for the dissection of brain tissues in MR image. Some of them are usual pattern recognition methods, rule-based systems, image investigation methods, hard and vague clustering procedures, feed-forward neural networks, fuzzy reasoning, geometric models to identify lesion boundaries, connected component analysis, deterministic annealing, atlas based techniques, and contouring approaches. Besides, recognition and analysis of the lesions manually from MR brain images are generally time consuming, expensive .The segmented MR images used in the medical diagnostic procedure depends on a combination of two, often contradictory, requirements, that is, the removal of the unnecessary evidence present in the original MR images and the conservation of the significant details in the resulting segmented images [3].

2. Literature Survey

Wang and Chen [4] used the grouping technique called Vector Seeded Region Growing (VSRG).In this methodology the seed pixel vectors are carefully chosen using Standard deviation and relative Euclidean distance. Using this processing the data dimensionality has been condensed. Trials are carried out and compared for performance valuation.

Cherradi et al. [5] advised an automatic approach for the separation of anatomical 3D brain MR images. This technique comprises many important steps,

1. Noise lessening using median filtering.
2. Division of brain/nonbrain tissue using a threshold morphologic brain abstraction technique (TMBE).

Followed, initial centroids approximation by gray level histogram analysis and this stage yields to a modified version of fuzzy C-means algorithm (MFCM) that has been executed for MRI tissue segmentation. Finally, 3D picturing of three clusters such as CSF, GM, and WM has been performed. Wide segmentation tests are done to confirm the proficiency of this method. This technique has attained a gain in rapidity of conjunction of about 70%.

The authors Rajendran and Dhanasekaran [6] did the separation of MRI brain image using Possibility Fuzzy c-means (PFCM) clustering technique. Execution of this technique to MRI brain has created better segmentation effect than the fuzzy-c means (FCM) and fuzzy possibility c mean (FPCM) algorithms. The effects have confirmed through several similarity metrics, false positive volume function (FPVF), and false negative volume functions (FNVF). The product values have showed that this method successfully segmented the tissues by employing the membership and possibility functions.

Hussain et al. [7] recommended segmentation technique, using fuzzy inference system (FIS) and FFBNN. Both used the extracted image features as a contribution for the classification process. The FIS perform the classification process by using the extracted features. Five features have been extracted: two active statistical features and three 2D wavelet decomposition features. In segmentation, the tissues such as WM, GM, and CSF have been segmented from the normal MRI images and harmful tissues such as edema and tumor have been segmented from the anomalous images. The noncortical tissues in the normal images have been removed in the pre-processing stage. The performance of the segmentation technique has been analysed using various performance measures such as accuracy, specificity, and sensitivity and compared with K-means clustering and fuzzy ANN based segmentation techniques.

Here in the previous tissue segmentation method the authors had proposed a tissue classification method with Improved Particle Swarm Optimization (IPSO) and FFBNN to distinguish the tissues from the MRI images. It includes four stages namely, Tissue Segmentation: Tissues are segmented manually by MRI experts.Preprocessing is done using skull stripping method to remove dark rings and later the brain image tissues are segmented, which includes normal and abnormal tissue segmentation. Feature Extraction: In this paper seven features are extracted. Out of which two are histogram based, two are statistical and three from wavelet. The combination of these extracted features from the segmented images is used and discussed in [18].Heuristic feature selection by IPSONN: The optimal feature selection process is defined through initialization, parameters, fitness, velocity and position, stopping criteria in [18].Tissue classification by FFBNN: The function of the neural network is done in two steps in [18].Even if this method achieved 95% improvement in sensitivity and accuracy measures compared to its related work papers, this method lacks its quality when the number of vertices increase and also it consumes time also.

3. Proposed Methodology

Most real life problems have several keys and occasionally an infinite number of solutions may be possible. If a problem admits more than one solution, optimization can be attained by finding the best solution of the problem in terms of some performance criterion. The graph partitioning problem (GPP) deals with the partition of vertices in a certain number of blocks in such a way that the edge cut is minimized. While partitioning graph, a balance constraint that all blocks must be of the same weight should also be maintained. Thus, optimization techniques are considered necessary for best partition with optimized cut value. Here in this paper we focus on Particle Swarm Optimization. This optimization technique is characterized by the use of local search method, recursively applied to the solution of the problem.

3.1 Particle Swarm Optimization

Kennedy and Eberhart , developed swarm intelligence model inspired by birds flocking behaviour called as Particle Swarm Optimization (PSO) algorithm. The PSO has particles determined from natural swarms by combining self-experiences with social experiences using communications based on iterative computations. In PSO algorithm, a candidate solution is presented as a particle. To search out to a global optimum, it uses a collection of flying particles (changing solutions) in a search area (current and possible solutions) as well as the movement towards a promising area. PSO is a met heuristic since it makes hardly any assumptions about optimization of the problem and hence it can search incredibly large spaces of candidate solutions. More specifically, PSO does not use the gradient of the problem being optimized. Resemble to classic optimization methods such as gradient descent and quasi-Newton methods; PSO does not require that the optimization problem should be differentiable. Consider a scenario that a group of birds is randomly searching food in an area. There is only one piece of food in the area being searched. All the birds don't know exact location of food but after each iteration they know the distance from food. Hence the best strategy to reach to the food is following the bird which is nearest to the food. PSO pick up from this state and uses it to resolve the optimization problems. In PSO, each single solution is a 'bird' in the search space called as 'particle'. All the particles have fitness values which are estimated using fitness function to be improved and have velocities that direct the flying of the particles. The particles (solutions) fly through the problem space by following the recent optimum particles. PSO is initialized with a group of random particles and then searches for optima by updating generations. In each iteration, every particle is updated by following two "best" values. The first value is the best solution (fitness) which it has achieved so far. This value is called pbest. Another "best" value that is tracked by the particle swarm optimizer is a global best and called gbest. After judging the two finest values, the particle appraises its velocity and positions [8], [9], [10], [19].

3.2 Artificial Neural Networks

Artificial Neural Networks (ANN) is mathematical models inspired by the functioning of human brain in a simple and objective way. It is an information processing model, where information processing occurs via simple elements called neurons. Signals are passed over connection links between these neurons. Neural networks operate on the principles of learning from a training set. There exists a variety of neural network models and learning procedures. The process of selecting a suitable architecture for a required problem can be broadly classified into the following steps

- Fixing the architecture
- Training the network
- Testing the network

Regardless of the approach used to optimize the number of neurons in the hidden layer care needs to be taken since too many neurons will increase training times unnecessarily by making it more difficult to estimate suitable set of interconnection weights while too few neurons can cause difficulties in mapping input to output in the training set. Multi-Layer Perceptron is one of the most fundamental and proper type of ANN architecture for practical applications of model identification. It is stated from literature that different kinds of ANN architectures like Radial Basis Function, Recurrent Neural Networks do not offer any key improvement over MLP architecture. Both the accuracy of classification and a networks learning ability can be severely affected if the architecture is not suitable. Two well-known classes of neural networks that can be used for classification applications are feed forward networks and probabilistic networks. Of the two, feed forward have found to have maximum application and has thus been adopted in this paper. In a feed forward network the weighted networks feed stimulations only in the forward direction from the input layer to the output layer. The input neurons receive and process the input signals and send the output to other neurons in the network where this process is continued [11]. This kind of network where info permits one way over the network is known as a feed forward network. A three layered feed forward ANN also known as Multi-Layer Perceptron (MLP) along with a typical processing element, an activation function, and a threshold function embedded to its body. Back propagation networks (BPN) are many layered networks with the unseen layers of sigmoid transfer function. The transfer function in the hidden layers should be differentiable and thus, either log-sigmoid or tan sigmoid functions are typically used. In this study, the tan-sigmoid transfer function, 'tansig' is used for both the hidden layers and the output layer. They calculate a layer's output from its net input. Each hidden layer and output layer is made of artificial neurons, which are connected through adaptive weights. The training function selected for the network is 'trainlm'.This type of neural network is trained using a process of supervised learning in which the network is presented with a series of matched input and output patterns and the connection strengths or weights of the connections automatically adjusted to decrease the difference between the actual and desired outputs. Subsequently, the testing record set is offered to the trained model, to perceive how well the network has learnt and performed [12], [13], [14], [15].

The proposed classification technique consists of three stages namely

1. Conversion
2. Implementation
3. Selection and extraction

The methodology implements the PSO algorithm with some image segmentation techniques. It includes the above said stages to obtain the affected brain tumor regions. The first stage is to convert the input image into graph. The graph consists of pixels from the image as the vertices and their intensity differences represent the weight. Sorted heavy edge matching (SHEM) sorts the vertices of the graph in ascending order using their degrees to decide the order to visit for matching. We have matched the vertex *x* with vertex *y*, if there is an edge of maximum weight from vertex x to an unmatched vertex y. A core number of the vertex is a maximum order of core which contains that vertex [16].To find the core number, the vertices of the graph are to be arranged in ascending degrees, then for each vertex y identified the vertices adjacent to y whose degree is greater than y. Degree of all such vertices is reduced by 1.The process continued until all vertices get core number [17]. Greedy Graph Growing Partition algorithm generates better result for any choice of the initial vertex to move.

The second stage is implementing the PSO algorithm. To achieve superior quality of approximate solutions of partitioning problems of graphs, a multilevel partitioning method is combined with PSO in this paper. The flowchart of PSO is shown in Figure 1.The implementation starts with initializes population on the smallest graph. Followed by the particles are successively projected back to the next level finer graph. Later recursively partitions the bisected graph into k-parts [19].

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The third stage, selection and extraction includes the separation of normal brain tissues such as Graymatter (GM),White Matter(WM) and Cerebro Spinal Fluid(CSF) and abnormal brain tissues such as edema ,tumor etc. The selected features are later given to the FFBNN classifier for training process.

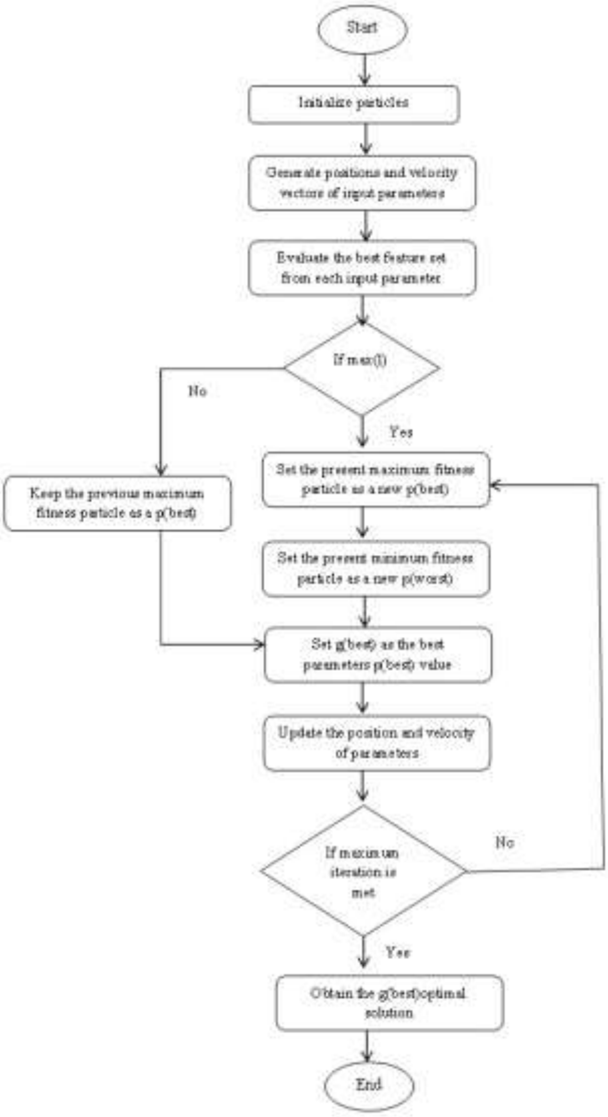


Figure 1: Flowchart of PSO

The structure of the algorithm is as follows:

Step1: Convert the input images into graph.

Step2: Coarsen using Sorted Heavy Edge Matching.

Step3: Greedy Graph Growing generates better result for initial choice of vertex to move.

Step4: Implement the PSO.

Step5: Recursively partitions the bisected graph into k-parts.

Step6: Feature selection and extraction is done and trained using FFBNN.

4. EXPERIMENTAL RESULTS

The detection and identification of brain diseases through the proposed method and the extraction of abnormal areas are carried out in this research work. This work takes the MRI of brain as input. Figure 2 represents the input. Figure 3 represents the manually segmented brain tissues. Segmentation of brain MRI into WM, GM, CSF, edema, tumor using the proposed technique is shown in Figure 4.

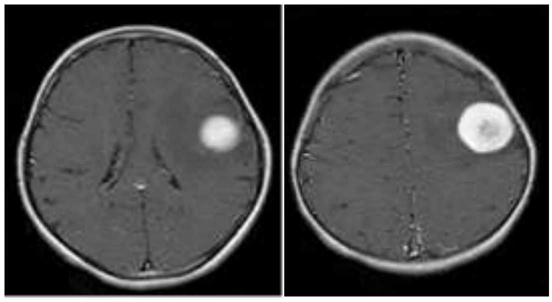
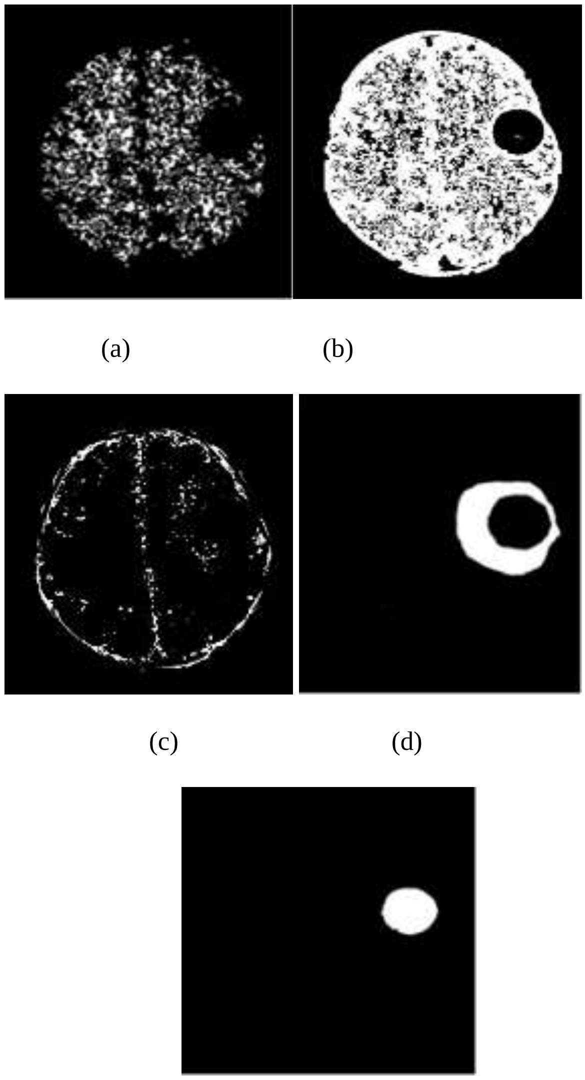


Figure 2: Sample Input MRI of brain



(a) (b)

(c) (d)

(e)

Figure 3: MRI brain tissues – segmented manually (a) WM, (b) GM, (c) CSF, (d) edema, (e) tumor

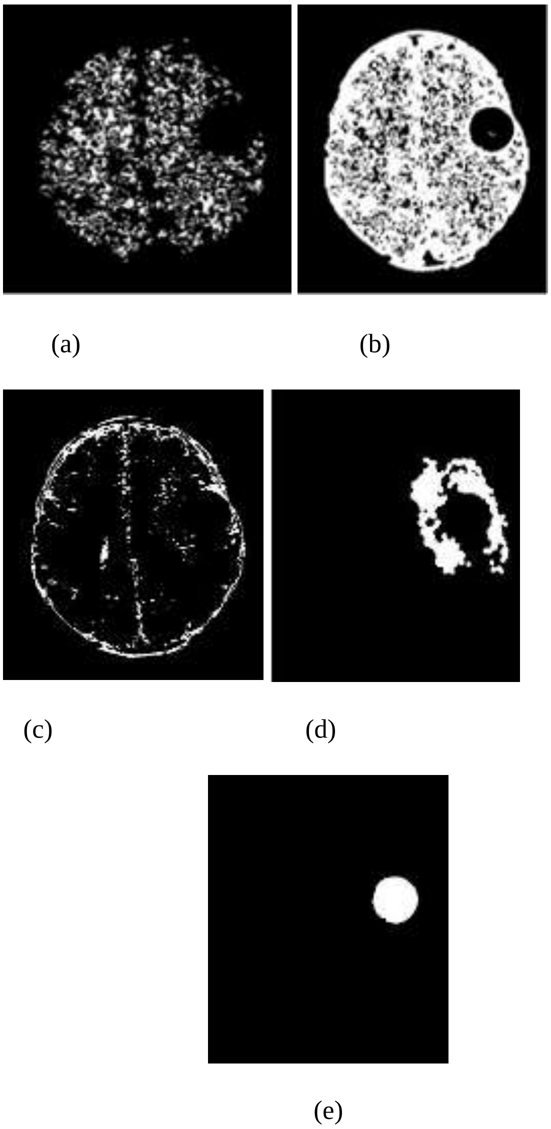


Figure 4: Segmentation of Brain MRI using proposed method (a) WM, (b) GM, (c) CSF, (d) edema, (e) tumor

The performance of proposed tissue classification method is analyzed by the statistical measures. The accuracy obtained in classifying the normal and abnormal tissues is shown in table 1 below.

Table 1: Performance of the proposed method in classifying (i) WM, (ii) GM, (iii) CSF, (iv) edema, (v) Tumor from Brain MRI

	WM	GM	CSF	edema	tumor
T_p	1	1	1	1	1
F_p	0	1	0	1	0
T_n	4	3	4	3	3
F_n	0	0	0	0	1
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

5. CONCLUSION

In this paper, we proposed a new tissue classification method to classify the normal and abnormal tissues from the MRI images. The method was implemented and a smaller set of MRI brain images were utilized to analyse the results of the classification method. In future works, the results presented in this paper should be extended and verified using larger and diverse image datasets.

REFERENCES

[1] Dhanya G.S and Sam Silva.A,"MRI Brain Images- A relative study between HGNN and IPSONN",International Journal of Innovative Science and Research Technology (ISSNNo:-2456-2165), vol 2,Issue 3,pp.79-82, Paper ID :IJISRT17MA31, March-2017.

[2] S.MahalekshmiandT.Velmurugan,"Detection of Brain Tumor by Particle Swarm Optimization using Image Segmentation",Indian Journal of Science and Technology(ISSN:0974-5645),vol 8(22),pp. 13-19,September ,2015

[3] Amita Kumari,Rajesh Mehra,"Hybridized Classification of Brain MRI using PSO & SVM" ,International Journal Of Engineering and Advanced Technology (ISSN:2249-8958) vol3,Issue 4,pp 319-323,April ,2014

[4] C.-M. Wang and R.-M. Chen, "Vector seeded region growing for parenchyma classification in brain MRI," International Journal of Advancements in Computing Technology, vol. 3, no.2, pp. 49–56, 2011.

[5] B. Cherradi, O. Bouattane, M. Youssfi, and A. Raihani, "Fully automatic method for 3D T1-weighted brain magnetic resonance images segmentation," International Journal of Image Processing, vol. 5, no. 2, pp. 220–235, 2011.

[6] Rajendran and R. Dhanasekaran, "MRI brain image tis- sue segmentation analysis using possibilistic fuzzy C-means method," International Journal on Computer Science and Engineering, vol. 3, no. 12, pp. 3832–3836, 2011.

[7] J. Hussain, S. Savithri, and S. Devi, "Segmentation of tissues in brain MRI images using dynamic neuro-fuzzy technique," International Journal of Soft Computing and Engineering, vol. 1, no. 6, pp. 416–423, 2012.

[8] Riyazul Haque, Shrikant Lade, Dayashankar Pandey, "Classification of MRI images using Particle Swarm Optimization Based Support Vector Machine for Tumor detection",COMPUSOFT,An international journal of advanced computer technology(ISSN:2320-0790),5(12), vol 5,Issue12,pp. 2245-2253,Dec.2016.

[9] Iman Behravan,Oveis Dehghantanha,Seyed Hamid Zahiri and Nasser Mehrshad," An optimalSVM with feature selection using Multiobjective

DOI: 10.18535/ijecs/v6i6.13

PSO",Journal of Optimization (Volume 2016),Article ID 305043,8 pages

[10] R.Bharathi, Dr.Divya Satheesh,"Improving MRI brain tumor classification and segmentation based on comparison technique",International Journal of Emerging Technology in Computer Science and Electronics(ISSN:0976-1353),vol 13,Issue 1,pp 560-569,March,2015.

[11] Margrave F.W., Rigas K., Bradley D.A. and Barrocliffe P. (1999), 'The use of neural networks in ultrasonic flaw detection',Measurement, Vol. 25, pp. 143-154.

[12] Prof.Vrushali Borase, Prof.Gayatri Naik, Prof.Vaishali Londhe, "Brain MR Image segmentation for Tumor detection using Artificial Neural",International Journal of Engineering and Computer Science(ISSN:2319-7242)",vol 6,Issue 1,pp. 20160-20163,Jan.2017.

[13] Selvaraj, D., Dhanasekaran, R., (2012): "MRI brain tumour detection using feed-forward neural network," Proceedings of EXCITE 2012, pp.171-174.

[14] Sheejakumari and A. Gomathi, "Healthy and pathological tissues classification in MRI brain images using hybrid genetic algorithm-neural network (HGNN) approach," European Journal of Scientific Research, vol. 87, no. 2, pp. 212–226, 2012.

[15] J. Kennedy and R. Eberhart, "Particle swarm optimization," in the Proceedings of IEEE International Conference on Neural Networks, Perth, Australia, Vol. 4, pp. 1942-1948, 1995.

[16] K. Schloegel, G. Karypis, V. Kumar, J. Dongarra, I. Foster, G. Fox, K. Kennedy, A. White, and M. Kaufmann, "Graph partitioning for high performance scientific simulations," 2000.

[17] J. Healy, J. Janssen, E. E. Milios, and W. Aiello. Characterization of graphs using degree cores. In WAW, 2006

[18] V.Sheejakumari and Sankara Gomathi, "MRI Brain Images healthy and pathological tissue classification with aid of Improved Particle Swarm Optimization and Neural Network (IPSONN)", Computational and Mathematical Methods in Medicine Volume 2015 (2015), Article ID 807826, 12 pages.

[19] Dhanya .G.S , Dr. R. Joshua Samuel Raj, P. Sivasamy ," Image Segmentation Using Swarm Intelligence Based Graph Partitioning,"IOSR Journal of Electronics and Communication Engineering -IOSR-JECE(e-ISSN: 2278-2834,p-ISSN: 2278-8735), pp.17-22, The National Symposium on Antenna Signal Processing & Interdisciplinary Research in Electronics 2017(ASPIRE-2017).

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