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MRI Brain Abnormality Detection using MLRPNN.

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ABSTRACT

In our proposed method, an automatic brain tumour segmentation and classification system is developed. The input image is preprocessed, segmented and features are extracted. Based on the extracted features, the input image is classified as cancerous or non-cancerous image using multilayer resilient propagation neural network classifier. In the preprocessing stage, noise is removed using median filter and the skull is stripped using morphological operators. Using thresholding technique and orthogonal polynomial transform, the skull stripped image is segmented into gray matter, white matter, cerebrospinal fluid and tumour. Then features like mean, variance, energy, and entropy are calculated. Later, multilayer resilient propagation neural network (MLRPNN) is trained with extracted features. A total of 150 images have been used, out of which 60 are used for training and remaining 90 images for testing. MLRPNN classifier classifies the input image to be cancer affected or normal based on features extracted. If the image is cancer affected, then type of cancer is detected as malign tumor or benign tumor using another MLRPNN Classifier. The performance of the proposed technique is validated and compared with the standard evaluation metrics such as sensitivity, specificity and accuracy values for neural network. The proposed method is compared with two standard methods KNN and FCM+NN. The obtained result depicts that the proposed classification method yields better results.

Keywords: Brain segmentation, Feature Extraction, Neural Network, Brain Tumor

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INTRODUCTION

The primary goal of MRI brain image segmentation is to partition a given brain image in to true anatomical structures representing such as grey matter, white matter, cerebrospinal fluid, skull and scalp. Later, the abnormalities in these tissues are detected. Identification and segmentation of brain tumor in magnetic resonance images is very crucial in medical diagnosis because it gives information related to anatomical structures as well as potential abnormal tissues necessary for treatment planning and patient follow-up. Precise segmentation of brain tumor is also useful for general modeling of pathological brains as well as the creation of pathological brain atlases [1, 2].

There is a variation in the signal intensities for the same tissues for different persons [3]. Although there are several approaches for MRI Brain image segmentation: discriminant analysis [4], neural networks [5,6], clustering [7], brain atlases [8], knowledge-based techniques [9], shape-based models [10,11], morphological operators [12], multivariate principal component analysis, pixel based models like Expectation Maximization Algorithm [13], Multi-resolution edge detection [5] and statistical pattern recognition [14], to name a few. Precise segmentation and classification of abnormalities are still a challenging and complicated task because of inherent noise, partial volume effect, different shapes, locations and image intensities of different types of tumors.

Manual segmentation cannot be compared with the current high speed computing machines that allow us to visually observe the size and position of the superfluous tissues. Supervised segmentation methods have exhibited problems with reproducibility, due to significant intra and inter-observer variance introduced over multiple trials of training Furthermore; they are time consuming and require domain experts. Whereas, the accuracy of unsupervised segmentation methods are less and depend upon input image. So these limitations suggest the need for a fully automatic method for segmentation.

In this paper, we have presented an efficient detection technique for the tumor region in the Brain MRI images. Here, we have utilized the brain tissue segmentation technique that proposed in research paper [15, 16, 17]. In addition with that, we have detected the tumor region with the aid of the regionprops algorithm [18]. Subsequently, the features vectors of all the segmented regions of the brain MR Image are calculated. Then, the abnormality classification is carried out by means of multilayer resilient propagation neural network.

PROPOSED METHOD

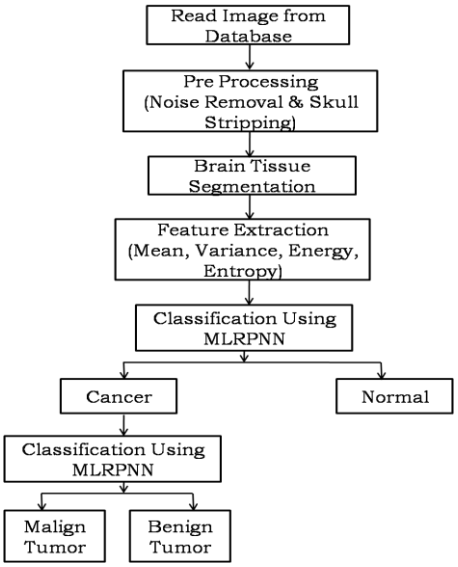

Figure 1: The flowchart of proposed approach

Our proposed method consists of 4 phases namely preprocessing, segmentation, feature extraction and classification. In preprocessing phase, the noise is removed using median filter and the skull is stripped

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using morphological operators and thresholding technique. Later, the skull stripped image is segmented into gray matter and white matter using thresholding technique. Orthogonal polynomial transform is used to segment cerebrospinal fluid. After segmentation process, the features such as Mean, Variance, Energy and Entropy are extracted from the regions and given to the MLRPNN classifier for training. Later, the image is classified as tumourous or normal with the help of trained MLRPNN. Finally, the type of cancer is detected using another MLRPNN classifier as detailed in Fig. 1.

The obtained experimental results by our proposed technique in research paper [15,16, 19] are as shown in Fig 2 and Fig 3. Here, we have given all the outcomes of the input image with and without tumour region.

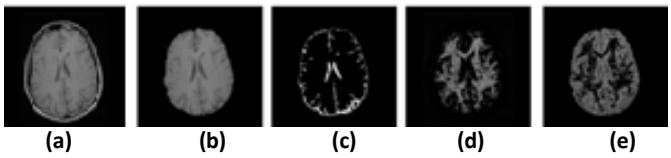

Figure 2: Segmented results of Brain MRI without Tumor. (a) Input Brain MR Image, (b) Skull Stripped Image, (c) Cerebrospinal Fluid Image, (d) White Matter, (e) Gray Matter

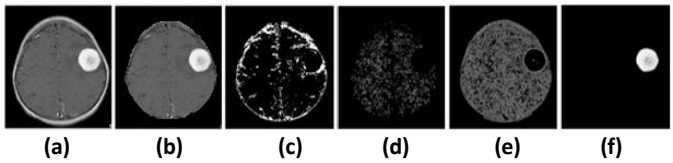

Figure 3: Segmented results of Brain MRI with Tumor. (a) Input Brain MR Image, (b) Skull Stripped Image, (c) Cerebrospinal Fluid Image, (d) White Matter, (e) Gray Matter, (f) Tumor Region

Feature Extraction From The Segmented Tissues

The analyzing methods have been done so far has used the values of pixels intensities, pixels coordinates and some other statistic features namely mean, variance or median, which have much error in determination process and low precision and efficiency in classification [19] . Here, the statistic features we have chosen are Mean M, Variance σ 2, Entropy E and Energy E (E,V,D) functions. The feature extraction process is carried out with some initial pre-processing. Each tissue segmented image is split into a limited number of blocks and the feature values are calculated for every block. The block diagram of the feature extraction process is given in Fig. 4. The initial steps are as follows:

- Find the neighbor blocks of the entire divided blocks.
- Find the distance between all the neighbor blocks.
- Find the feature values of the blocks with distinct distance measure.
- Find the average value of all the computed blocks distance.
- Store all the features in a vector and fed as an input to the classifier.

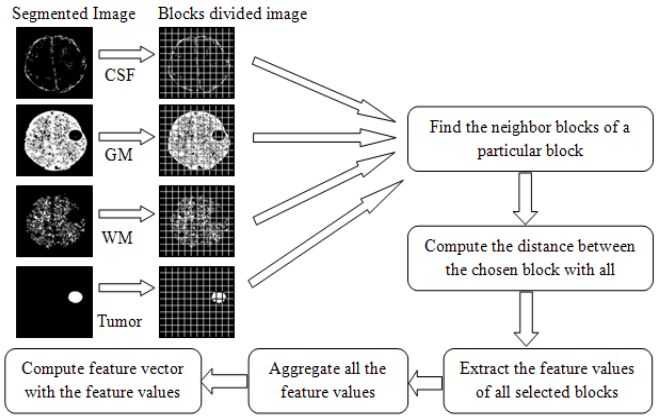

Figure 4: Block diagram of Feature Extraction Process

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The statistic feature's formula is depicted as below,

$$\text{Mean, } M = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{m} x(i,j) \quad (1)$$

$$\text{Variance, } \sigma^2 = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(x(i,j)-M)^2 \quad (2)$$

$$\text{Entropy, } E = -\sum_{i}\sum_{j} x(i,j)\log x(i,j) \quad (3)$$

$$\text{Energy, } E_{(H,V,D)} = \sum_{i}\sum_{j} x(i,j)^2 \quad (4)$$

Selection of efficient features can reduce significantly the difficulty of the classifier design. The obtained trained feature is compared with the test sample feature obtained and classified as one of the extracted features. The training feature vector Fv is defined by combining all the extracted features like mean M, variance σ 2, entropy E and the energy E(H,V,D). In order to obtain the three wavelet energies, the Haar wavelet transform is applied to each blocks of brain MR Image. After a one level wavelet transform, a 4×4 pixel block is decomposed into four frequency bands of 2×2 coefficients. For example, the coefficients in horizontal band of one block are H1, H2, H3, H4, in vertical band V1, V2, V3, V4 and in diagonal band D1, D2, D3 and D4. Then horizontal energy EH, vertical energy EV and diagonal energy ED are combined to attain the feature value of the energy.

$$\text{Feature Vector, } F_v = [f(M), f(\sigma^2), f(E), f(E_H), f(E_V), f(E_D)] \quad (5)$$

Brain image classification using MLRPNN

The classifiers we have used here is MLRPNN. The general structure of MLRPNN is shown in Fig. 5. In MLRPNN, the data flows from input layer to the output layer through the hidden layers in the forward direction. The network consists of 1 input layer with 24 neurons, 1 output layer with one neuron and 2 layers of hidden units with 10 neurons. The algorithm used to train the network is resilient propagation algorithm.

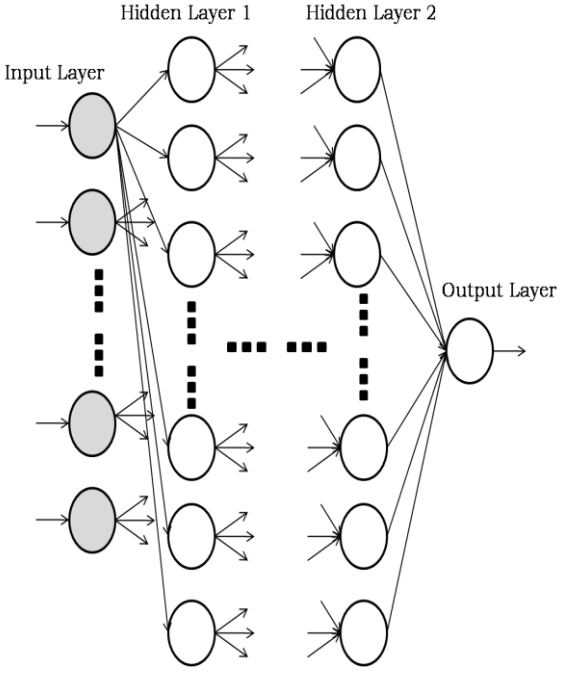

Figure 5: General Structure of MLRPNN

Each hidden node calculates the weighted sum of its inputs and applies a thresholding function to determine the output of the hidden node. The weighted sum of the inputs for hidden node Z_h is calculated as,

$$Z_h = \sum_{i=0}^{n} W_{hi} x_i \quad (6)$$

The thresholding function applied at the hidden node is a sigmoid function. The general form of the sigmoid function is

$$\text{Sigmoid}(a) = \frac{1}{1+e^{-a}} \quad (7)$$

The sigmoid function is also called as squashing function, because it squashes its input to a value between 0 and 1. So, the output of hidden node is given as,

$$Z_h = \text{Sigmoid}\left(\sum_{i=0}^{n} W_{hi} x_i\right) = \frac{1}{1+e^{-\sum_{i=0}^{n} W_{hi} x_i}} \quad (8)$$

Similar computation is done for the next hidden and output units. We have only one output unit in the output layer. So, the following sigmoid function (equation 9) is applied to the output unit.

$$y = \text{Sigmoid}\left(\sum_{h=0}^{N} V_h z_h\right) = \frac{1}{1+e^{-\sum_{h=0}^{N} V_h z_h}} \quad (9)$$

The algorithm used to train the neural network is resilient propagation algorithm. This algorithm is the modified algorithm of standard back propagation algorithm. In this algorithm, the weight updating method of standard back propagation algorithm is modified. The size of the weight change is determined by the update value.

$$\Delta W_{ij} = -Sign\left(\frac{\partial E}{\partial W_{ij}}\right)\Delta_{ij} \quad (10)$$

Where, Δij is an update value which evolves during the learning process according to the following rule.

RPA Learning Rule:

$$\Delta_{ij}(t) = \begin{cases} \eta^{+}.\Delta ij(t-1); if\ S_{ij} > 0 \\ \eta^{-}.\Delta ij(t-1); if\ S_{ij} < 0 \\ \Delta ij(t-1); Otherwise \end{cases} \quad (11)$$

$$Where,\ \ Si_j = \frac{\partial E}{\partial W_{ij}}.(t-1).\frac{\partial E}{\partial W_{ij}}(t); \eta^{+} = 1.2; \eta^{-} = 0.5$$

RPA Weight Step Rule:

$$\Delta W_{ij}(t) = \begin{cases} -\Delta_{ij}(t); if\ R_{ij} > 0 \\ +\Delta_{ij}(t); if\ R_{ij} < 0 \\ 0;\ Otherwise \end{cases} \quad (12)$$

$$Where,\ \ R_{ij} = \frac{\partial E}{\partial W_{ij}}.(t)$$

A simple rule is followed for the weight update: if the derivative is '+ve' (increasing error), the weight is decreased by its update value and if the derivative is '-ve', the update value is added.

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EXPERIMENTAL RESULTS AND DISCUSSION

We have presented a technique for segmentation and detection of pathological tissues (Tumor), normal tissues (White Matter and Gray Matter) and fluid (Cerebrospinal Fluid) from magnetic resonance (MR) images of brain with the help of composite feature vectors comprising of wavelet and statistical parameters. The proposed technique can successfully segment the tumors as well as the brain tissues, provided that the parameters are set properly. The proposed technique is designed for supporting the tumor detection in brain images with tumor and without tumor. The obtained experimental results from the proposed technique are given in Fig. 6 and Fig. 7. In Fig. 6 and Fig. 7, the segmented normal tissues (CSF, WM, GM) and pathological tissues (tumour) of MRI brain image with and without tumor is shown. The feature values calculated for these segmented tissues using block based feature extraction method is tabulated in table 1.The simulation result of neural network training dataset is as shown in Fig 8 to Fig 11.

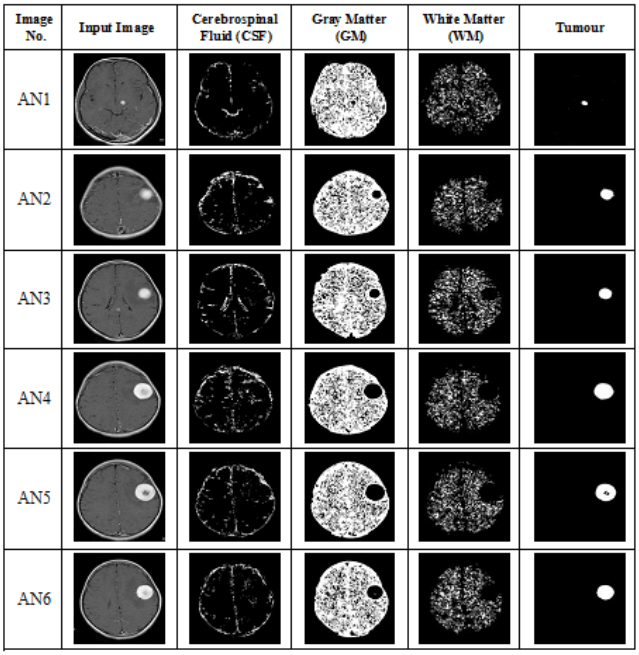

Figure 6: Segmented normal tissues (CSF, GM, WM) and pathological tissues(tumor) of MRI brain images with tumor

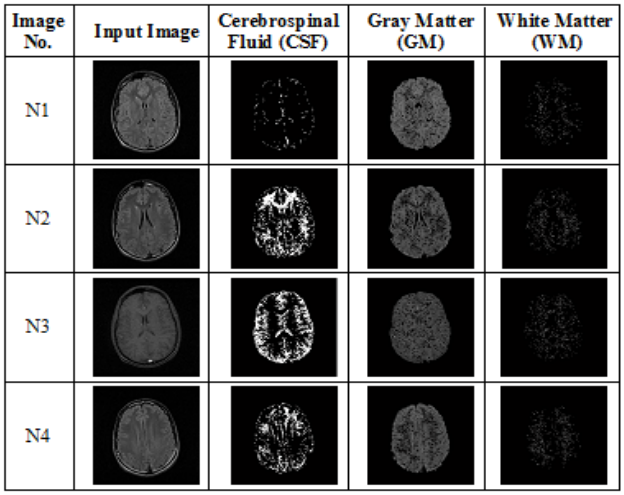

Figure 7: Segmented normal tissues (CSF, GM, WM) and pathological tissues(tumor) of MRI brain images without tumor

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Table I: Feature values extracted from segmented tissues of MRI brain images

Image No.	Tissue	Feature Values					
		Mean	Var	Ent	Energy		
					Horiz.	Verti.	Diag.
AN1	CSF	0.43	0.157	0.74	1.67	1.60	1.32
	GM	68.41	819.28	0.43	12.62	12.18	9.67
	WM	33.9	1311.07	0.73	15.73	15.22	13.05
	Tumor	180.4	1609.4	0.3	20.9	12.20	7.2
AN2	CSF	0.46	0.14	0.68	1.63	1.60	1.34
	GM	66.87	946.97	0.47	13.31	12.49	10.2
	WM	37.13	1369.71	0.72	15.92	15.00	13.01
	Tumor	181.48	935.04	0.18	12.68	11.77	7.80
AN3	CSF	0.51	0.14	0.67	1.58	1.53	1.14
	GM	69.40	861.86	0.43	12.94	11.94	9.62
	WM	35.48	1315.72	0.72	16.04	15.07	13.01
	Tumor	151.10	829.26	0.22	12.21	11.79	7.22
AN4	CSF	0.49	0.14	0.67	1.54	1.53	1.21
	GM	65.82	895.11	0.47	13.12	12.33	10.03
	WM	37.26	1340.49	0.72	15.84	14.96	12.96
	Tumor	151.10	829.26	0.22	12.21	11.79	7.22
AN5	CSF	0.45	0.15	0.68	1.66	1.48	1.18
	GM	67.55	938.78	0.47	13.29	12.39	10.03
	WM	36.24	1355.65	0.72	15.95	15.15	12.96
	Tumor	180.57	925.29	0.17	12.48	11.41	7.51
AN6	CSF	0.46	0.15	0.71	1.51	1.55	1.34
	GM	66.23	899.19	0.47	13.01	12.54	9.99
	WM	36.67	1348.12	0.73	15.69	15.26	12.91
	Tumor	151.00	906.38	0.24	11.97	12.10	8.06
N1	CSF	0.53	0.14	0.67	1.52	1.5	1.19
	GM	54.40	430.72	0.4	10.79	10.48	8.18
	WM	24.21	825.47	0.74	14.34	13.84	11.84
	Tumor	41.38	4272.17	0.67	23.31	11.75	8.11
N2	CSF	0.22	0.13	0.62	1.5	1.52	1.43
	GM	75.30	397.43	0.26	10.27	10.79	7.56
	WM	28.22	1077.17	0.73	15.29	15.27	12.83
	Tumor	91.16	2965.07	0.65	18.32	21.57	18.55
N3	CSF	0.28	0.14	0.73	1.53	1.52	1.37
	GM	86.64	1044.9	0.37	12.58	13.06	9.84
	WM	52.44	2138.11	0.71	17.67	18.05	14.80
	Tumor	82.07	2187.05	0.60	16.65	16.37	13.67
N4	CSF	0.53	0.12	0.62	1.37	1.43	1.17
	GM	59.09	380.3	0.36	10.42	11.21	8.00
	WM	26.17	750.23	0.73	13.57	13.93	11.57
	Tumor	71.41	3648.76	0.73	20.56	17.98	19.37

The segmentation result is evaluated with the help of quality rate given as follows,

$$\text{Quality rate, } q_r = area(A \cap B) / area(A \cup B) \qquad (13)$$

The evaluation of brain tumor detection in different images is carried out using the following metrics,

$$\text{Sensitivity} = TP/(TP+FN) \qquad (14)$$

$$\text{Specificity} = TN/(TN+FP) \qquad (15)$$

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$$\text{Accuracy} = (TN+TP)/(TN+TP+FN+FP) \qquad (16)$$

Where, TP stands for True Positive, TN stands for True Negative, FN stands for False Negative and FP stands for False Positive. Table 2 defining the relevant terms of the evaluation metrics like TP, FP, FN, and TN.

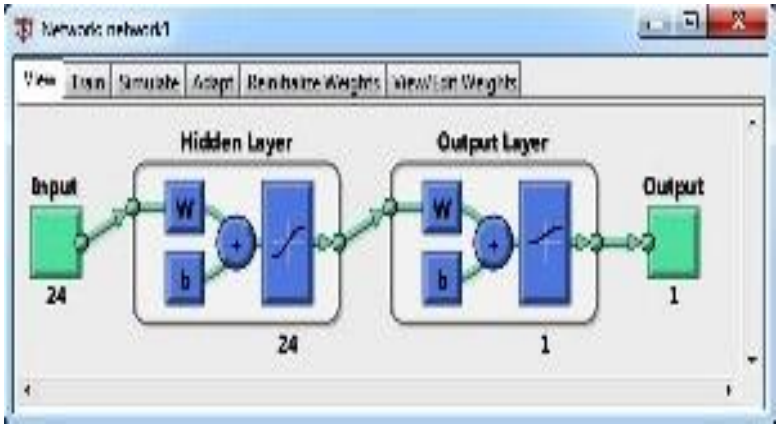

Figure 8: Structure of MLRPNN

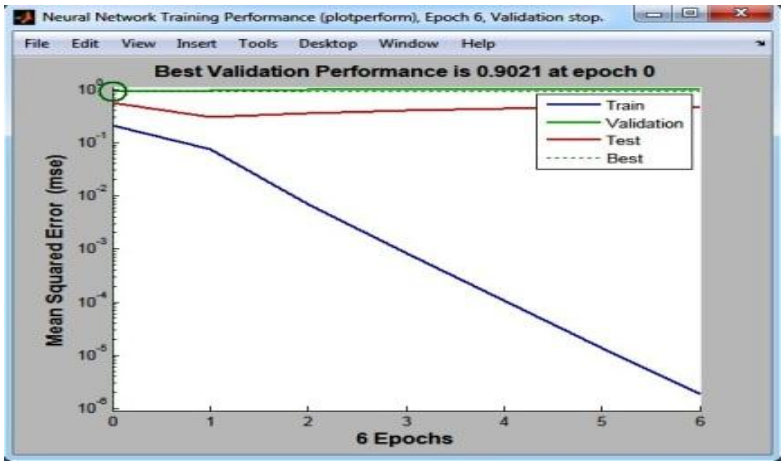

Figure 9: Performance validation of MLRPNN

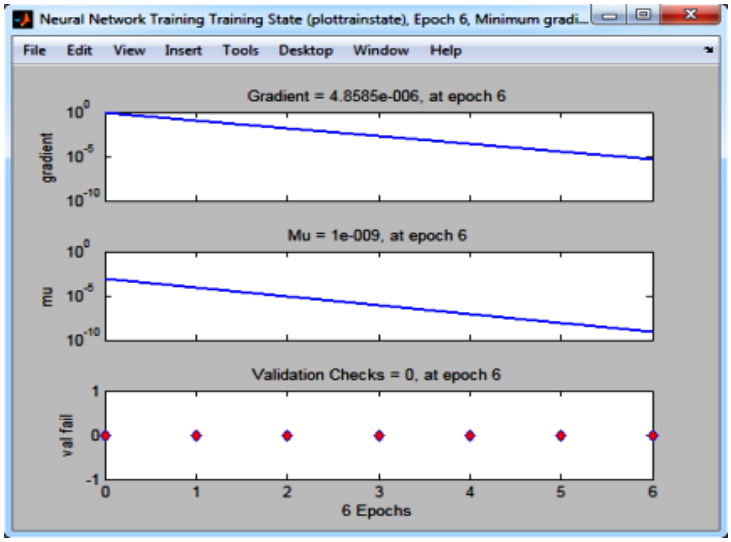

Figure 10: MLRPNN training state

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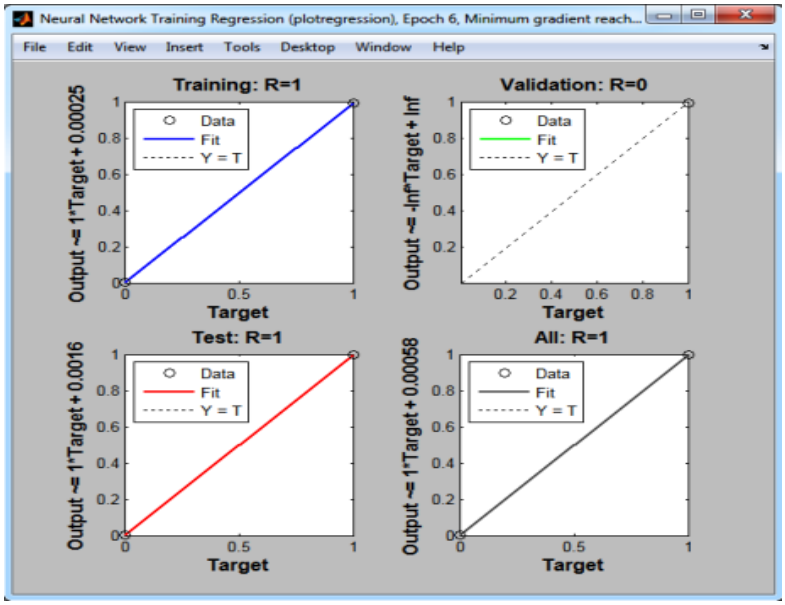

Figure 11: MLRPNN training Regression Plot

Table II: Table defining the terms TP, FP, FN, TN

Experimental Outcome	Condition		Row Total
	Positive	Negative	
Positive	TP	FP	TP+FP
Negative	FN	TN	FN + TN
Column total	TP+FN	FP+TN	N=TP+TN+FP+FN

With the aid of the input MR image training and testing dataset, the values of TP, TN, FN, FP, specificity, sensitivity, and accuracy is given in Table III & IV. The results show that the accuracy is 83.33%. The evaluation metrics are also compared with the standard methods like KNN and neural network combined with FCM. The evaluation metrics table shows that our proposed method is more accurate than other two methods.

Table III: Detection accuracy of the proposed method in training dataset

Evaluation Metrics	Proposed Method (MLRPNN)	Previous Proposed Method (MLBPNN)	KNN	FCM + NN
True Negative	43	43	41	42
False Positive	0	0	2	2
True Positive	16	16	15	12
False Negative	1	1	2	4
Specificity	100.00%	100.00%	95.35%	95.45%
Sensitivity	94.12%	94.12%	88.24%	75.00%
Accuracy	98.33%	98.33%	93.33%	90.00%

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Table IV: Detection accuracy of the proposed method in testing dataset

Evaluation Metrics	Proposed Method (MLRPNN)	MLBPNN	KNN	FCM + NN
True Negative	50	50	46	46
False Positive	10	10	13	15
True Positive	25	25	22	25
False Negative	5	5	9	4
Specificity	83.33%	83.33%	77.97%	75.41%
Sensitivity	83.33%	83.33%	70.97%	86.21%
Accuracy	83.33%	83.33%	75.56%	78.89%
Execution Time (Sec)	44	93	88	170

The experimental results for normal and abnormal classification are listed in table III and IV. Table IV table shows that our proposed method is more accurate when compared to the other standard methods. The result showed that MLBPNN and MLRPNN produce the same accuracy. But the execution time of MLRPNN is less when compared to MLBPNN. Once again, MLRPNN was used to classify the abnormal image as benign or malignant. The results for benign or malignant are tabulated in table VI. For our neural network 24-24-10-1, the average execution time is tabulated in table V showing the difference in execution time between MLBPNN and MLRPNN.

Table V: Average Execution time for 24-24-10-1 NN

Method	Epochs	SD	ExecutionTime
MLBPNN	114	28	93 sec
MLRPNN	23	3	44 sec

Table VI: Tumour Classification

Type	Benign	Malignant
Benign	39	2
Malignant	1	29

CONCLUSION

In this paper, we have presented an effective neural network classifier to identify normal and abnormal (Benign or Malignant) brain images. We have taken 150 images (40 normal, 60 malignant and 50 Benign). The performance of the proposed technique is evaluated by means of the evaluation metrics namely, Sensitivity, Specitivity and Accuracy. The comparative analysis is also carried out with standard methods like KNN, FCM+NN and with our previously proposed method. Our current proposed method (MLRPNN) produced the same accuracy as previously proposed method (MLBPNN) but the execution time is twofold reduced. So, the obtained result shows that the proposed method produces better results than the other classifiers in terms of accuracy as well as in terms of execution time.

REFERENCES

[1] T. Logeswari and M. Karnan, "An improved implementation of brain tumor detection using segmentation based on soft computing", Journal of Cancer Research and Experimental Oncology Vol. 2, No: 1, pp. 006-014, March, 2010.

[2] A.W. Toga, P. M. Thompson, M. S. Mega, K. L. Narr, R. E. Blanton, "Probabilistic approaches for atlasing normal and disease-specific brain variability, Anatomy and Embryology", Vol: 204, No: 4, pp: 267–282, 2001

[3] C. A. Parra, K. Iftekharuddin and R. Kozma, "Automated brain data segmentation and pattern recognition using ANN," in the Proceedings of the Computational Intelligence, Robotics and Autonomous Systems (CIRAS 03), December, 2003.

[4] Zavaljevski, A. Dhawan, A.P. Gaskil, M. Ball, W. and Johnson, J.D., "Multi-level adaptive segmentation of multiparameter MR brain images", Comput Med Imag Graphics, vol. 24, pp. 87–98, 2000.

[5] Suckling, J. Sdsson, T. Greenwood, K. and Bullmore, E.T., "A modified fuzzy clustering: algorithm for operator independent brain tissue classification of dual echo MR images", Magn. Reson. Imag., vol. 17, pp. 1065–1076. 1999.

[6] Alirezaire, J. Jernigan, M.E. and Nahmias, C., "Automatic segmentation of cerebral MR images using artificial neural networks", IEEE Trans Nucl Sci, vol. 45, pp. 2174–2182, 1998.

[7] I. Middleton and R. Damper, "Segmentation of Magnetic Resonance Images using a combination of Neural Networks and Active Contour Models," in Medical Engineering & Physics, No. 26, pp. 71-86, 2004.

[8] Nakazawa, Y. and Saito, T. Region extraction with standard brain atlas for analysis of MRI brain images", Proceedings of the IEEE International Conference on Image Process, vol.1, pp. 387–91, 1994.

[9] Clark, M.C. Hall, L.C. Goldgof, D.B. Velthuizen, R. Murtagh, F.R. and Silbiger, S.,"Automatic tumor segmentation using knowledge-based techniques", IEEE Trans. Med. Imag., vol. 17, pp. 187–201. 1998.

[10] Duta, N. and Sonka, M., "Segmentation and interpretation of MR brain images: an improved active shape model", IEEE Trans. Med. Imag., Vol. 16, pp. 1049–1062, 1998.

[11] Suri, J., "Two-dimensional fast Magnetic Resonance brain segmentation", IEEE Eng Med Biol, pp. 84–95, 2001.

[12] Chen, Y. Dougherty, E.R. Totterman, S.M. and Hornak, J.P., "Classification of trabecular structure in magnetic resonance images based on morphological granulometries", Magn. Reson. Med, vol. 29, pp. 358–370, 1993.

[13] Andersen, A.H. Zhang, Z. Avison, M.J. and Gash, D.M., "Automated segmentation of multispectral brain MR images", J. Neurosci Methods, vol. 122, pp. 13–23. 2002.

[14] T.K. Moon, "The Expectation Maximization Algorithm", IEEE Signal processing magazine, 1996.

[15] Selvaraj.,D., Dhanasekaran,R., " Novel approach for segmentation of brain magnetic resonance imaging using intensity based thresholding", 2010 IEEE international conference on communication control and computing technologies, pp 502-507, 7-9 october 2010.

[16] Selvaraj.,D., Dhanasekaran,R., " Segmenting internal brain nuclei in MRI brain image using morphological operators", 2010 International conference on computational intelligence and software engineering, pp 1-4, 10-12 December 2010.

[17] D. Selvaraj, R. Dhanasekaran, "Segmentation of cerebrospinal fluid and internal brain nuclei in brain magnetic resonance images," IRECOS, Vol.8, issue 5, 2013, pp.1063-1071.

[18] "Regionprops Algorithm" from http://www.mathworks.in/help/toolbox/images/ref/regionprops.html

[19] Carlos A. Parra, Khan Iftekharuddin and Robert Kozma, "Automated Brain Data Segmentation and Pattern Recognition Using ANN", Computational Intelligence, Robotics and Autonomous Systems (CIRAS 03), December 2003.