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Neuro-Fuzzy Inference System for Brain Tumour Classification

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Abstract:

Identification of brain tumour is an important task for diagnosis of the tumour. The proposed system is used to identify the correct type of tumour and classify it to the respective class label.

Keywords — **Type of Tumour Diseases, MRI, Feature Vector, Classification.**

I. INTRODUCTION

A tumour can be graded into several stages by the analysis of abnormality of the tumour cells and tissues. This grading gives us the acute probability of tumour growth in size and its spreading. Tumour grade can be determined using biopsy. Five major types of brain tumours:

1) Glioma, 2) Meningioma, 3) Metastatic adenocarcinoma, 4) Metastatic bronchogenic carcinoma, and 5) Sarcoma are considered for computerized classification.

A database has been created that contains images associated with its corresponding class label for testing and training the classifiers. Initially MRI Image is normalized and then extracted features are taken for classification. Proposed work exhibits the application of Fuzzy Inference System (FIS) based classifier known as Adaptive Neuro-Fuzzy Inference System (ANFIS) to successfully classify

the five major types of brain tumours. **Literature Reviews**

Many researchers have attempted to correctly classify brain tumours into appropriate types. A texture based analysis [1] on Gabor wavelets to improve the accuracy of classification was used in feature extraction steps and support vector machine-based classifier to classify the tumours. Another technique [2] of discrete wavelet transforms on the MRI slices to extract the features and then minimized using principal component analysis was used to classify brain tumour. In their work [3] two types of classifiers were used: feed forward back propagation neural network and K-nearest neighbours. Some hybrid models such as support vector machine recursive feature elimination (SVM-RFE) were used [4] for classification. Ranking based criterion that tests the discriminative power of each distinct feature was used as SVM-RFE to produces an optimal performance for the classifier. Segmentation of

region of interest before feature extraction has been done in some of the works [4].

MRI brain abnormalities segmentation study are formed by cutting various shapes and size of abnormalities and pasting it onto normal brain tissue [5]. The statistical analysis method of receiver operating characteristic (ROC) was used to calculate the accuracy. An automatic method [6] that integrates knowledge-based techniques with multispectral analysis for tumour labels identification. The results of the system correspond well to ground truth, both on a per state basis and more importantly in tracking total volume during treatment over time. The back propagation learning algorithm is a supervised learning method that can be used with multilayer networks and nonlinear differentiable transfer functions. Neural network and ANN perform much better when dealing with multi-dimensions and continuous features. In this paper, a FIS based adaptive neural network known as ANFIS is used to classify the major five types of brain tumour from standard datasets with accuracy estimations.

Proposed Methodology

Artifacts and skull elimination is used to remove unnecessary regions of MRI. Then they are normalized to a range for feature extraction process. After performing the training on a set of existing known data set then test the data for appropriate classes that help incorrect medical decision making and diagnosis of brain tumour. The brief implementation of the technique has been shown in the figure 1.

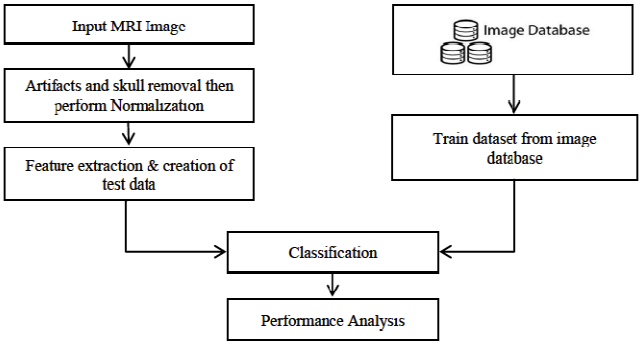

Figure 1: Workflow of the tumour classification

The images have been collected from brain atlas [7] and other mentioned dataset [6-7]. Now consider that $f(x,y)$ is the function that represents the intensity level for each pixel (x,y) in the image $x = 1,2,\cdots,A \quad y = 1,2,\cdots,B$. Grey-level histogram calculation involves each pixel. Probability density for each occurring pixel intensity level $0,1,\cdots,N-1$ is calculated dividing them with $h(i)$ by the total number of pixels.

Classification step occurs in two consecutive steps: a learning phase and testing phase. In learning phase it needsto build a model that can successfully classify a dataset. Back propagation algorithm is an optimization procedure based on gradient descent that adjusts the weights to reduce the system error. During the learning phase, input patterns are presented to the network, and the network parameters are changed to bring the actual outputs closer to the desired target values.

If there is any difference with target values then it is treated as errors. This errors are some scalar function of the weights and are adjusted to reduce errors.

Results

The training dataset is generated from image database [5-8]. In this processes, the images are normalized to the feature vector containing 12 features are extracted from the slices. This vector is generated for 20 input slices shown in Figure 2has been illustrated by Table 1 and Table 2.

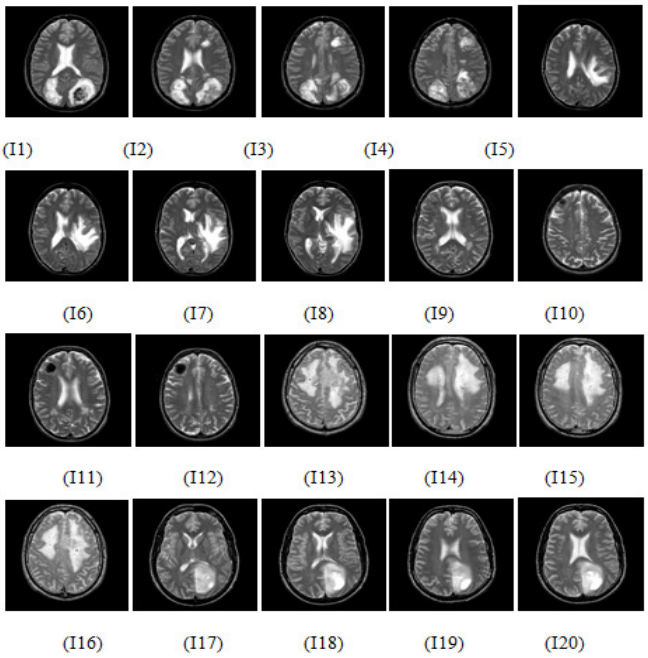

Figure 2: 20 input slices passed through the normalization and feature extraction processes for classification. After classification we found that slices I1-I4 are Type 1 (Sarcoma); slicesI5-I8 are Type 2 (Meningioma); slices I9-I12 are Type 3 (Metastatic adenocarcinoma); slices I13-I16 are Type 4 (Metastatic bronchogenic carcinoma);slicesI17-I20 are Type 5 (Glioma)

Each of the generated feature vector from the normalized grayscale image is calculated from 1st order histogram based features and features from Gray Level Co-occurrence Matrix. Table 1 and Table 2 show the feature vectors of the normalized grayscale image.

Table 1: Feature vector from the normalized grayscale MR image

Image sequence	Mean	Variance	Skewness	Kurtosis	Energy	Entropy
1	15.5399	446.433	0.000108	0.000127	0.2816	3.6817
2	14.7607	427.681	0.000126	0.000151	0.2933	3.5751
3	15.5426	447.411	0.000108	0.000127	0.2810	3.6939
4	15.3294	434.847	0.000116	0.00014	0.2762	3.7014
5	15.9980	466.920	0.0001	0.000118	0.2718	3.8210
6	16.2995	455.317	0.000972	0.000117	0.2540	3.8918
7	16.8535	461.050	0.000906	0.00011	0.2365	3.9722
8	15.2010	463.274	0.000113	0.000132	0.2981	3.6796
9	13.6257	406.182	0.00015	0.000185	0.3333	3.2856
10	13.9531	413.331	0.000143	0.000175	0.3219	3.4029
11	13.1538	400.748	0.000161	0.000200	0.3529	3.2298
12	14.2234	417.177	0.000137	0.000165	0.3123	3.4526
13	13.6782	420.489	0.000142	0.000167	0.3506	3.2687
14	13.5103	417.582	0.000144	0.000169	0.3583	3.1849
15	13.2064	412.893	0.000151	0.000178	0.3698	3.1134
16	12.3658	388.257	0.000181	0.000226	0.3857	3.0153
17	12.9241	397.207	0.000167	0.00021	0.3573	3.2094
18	13.5875	407.496	0.000151	0.000185	0.3342	3.3352
19	14.2193	425.415	0.000137	0.000164	0.3174	3.4692
20	14.9834	443.361	0.000118	0.000138	0.3040	3.5664

Table 2: Feature vector from the normalized grayscale MR image (continuation of Table 1)

Image sequence	Contrast	Correlation	Energy	Homogeneity	Inverse difference	Abs e va
1	0.3334	0.3878	0.4131	0.8726	56710.6	179
2	0.3190	0.3833	0.4379	0.8774	57036.6	172
3	0.3415	0.3862	0.4071	0.8697	56512.8	183
4	0.3547	0.3508	0.4112	0.8659	56247.2	189
5	0.3618	0.3884	0.3971	0.8663	56246	189
6	0.3499	0.3785	0.3871	0.8652	56218.6	189
7	0.3697	0.3640	0.3731	0.8592	55806.6	198
8	0.3610	0.3920	0.4227	0.8712	56534.6	185
9	0.2931	0.3803	0.4756	0.8861	57632.2	159
10	0.2984	0.3755	0.4668	0.8831	57439.6	163
11	0.2885	0.3749	0.4930	0.8896	57854	155
12	0.3019	0.3595	0.4589	0.8800	57245.4	166
13	0.2558	0.4260	0.4907	0.8970	58395.4	142
14	0.2565	0.4179	0.4908	0.8972	58406	142
15	0.2443	0.4349	0.5019	0.9011	58674.6	136
16	0.2395	0.4074	0.5274	0.9029	58796.6	134
17	0.2881	0.3883	0.4918	0.8902	57893.2	154
18	0.2936	0.3933	0.4727	0.8867	57670.4	158
19	0.3158	0.3685	0.4617	0.8804	57227	168
20	0.3164	0.3804	0.4429	0.8786	57115.6	170

Each tuple contains its class label which denotes its tumour type which is used to build IF-THEN rules to generate the FIS. An adaptive network is then built depending on the training tuples and the FIS. ANFIS is trained network that is used to generate the class label for the input slices. The class labels mentioned here were taken accordingly as: Class 1 = Sarcoma, Class 2 = Meningioma, Class 3 = Metastatic adenocarcinoma, Class 4 = Metastatic bronchogenic carcinoma, Class 5 = Glioma. The classifier gives fuzzy numbers as output which is de- fuzzified to get the crisp actual class labeled values. Performance measurement metrics value of 5 major tumour types as the different class has been shown in Table 3.

Table 3: Classification rates of an ANN classifier for brain tumour

Metric	Class 1	Class 2	Class 3	Class 4	Class 5
rue Positive (TP)	37	43	32	29	48
alse Negative (FN)	4	4	5	2	4
alse Positive (FP)	3	3	2	6	5
rue Negative (TN)	164	158	169	171	151
ensitivity(TP/(TP+FN))	0.902	0.914	0.864	0.935	0.923
pecificity(TN/(FP+TN))	0.982	0.981	0.988	0.966	0.967
recision(TP/(TP+FP))	0.925	0.934	0.941	0.828	0.905
ccuracy((TP+TN)/(P+N))	0.966	0.966	0.966	0.961	0.956
score(2TP/(2P+FP+FN))	0.913	0.924	0.901	0.878	0.914

Conclusions

Analysis with a large number of variables requires a large amount of memory and computation power or a classification algorithm which over-fits the training sample and also generalizes successfully to new samples. Automation of a model for computing an estimate of the type of tumour are verified by a radiologist, and a simultaneous measure of the quality of each phase assess the automated image classification and segmentation algorithm performance. The proposed system can help the physicians to identify the type of brain tumours for further treatment.

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