# CLASSIFICATION OF NORMAL AND ABNORMAL BRAIN IN MR IMAGES

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**Abstract- Traditionally radiologists are fully responsible for detection of brain anomalies in the MR images of the human brain. As the wrong prognosis in the case of brain tumors can be life threatening, automatic classification of brain MR Images requires high accuracy and precise diagnosis. As human intervention in interpretation of brain MR images can be effected by the experience and knowledge of radiologist's, automatic classification system is proposed for brain tumor MR image classification in order to assist them to have proper diagnosis. The present study discusses the effect of neural network (NN) algorithms for lesion classification. An MR Image data set which was benchmarked earlier was used in the present study. The results of experiments show that the present approach gives 96.5% accuracy using NN.**

*Keywords:* **Magnetic resonance (MR), Neural Network (NN), minimum Redundancy maximum Relevance (mRmR), Artificial Neural Network (ANN)**

## I. Introduction

Digital imaging is now extensively used in every scientific field such as criminology, forensics, biology, astronomy etc. It bears a valuable place in medical field. As brain being one of the most intricate organ, it always intrigues most researchers [1, 2].

MRI also called magnetic resonance tomography, visualizes in internals of the body by the use of images of high quality. It's distinct significance is in distinguishing the soft brain tissues over other imaging techniques [1, 2]. As accurate diagnosis of pathological and normal tissue is very important and image segmentation plays key part in the same. The segmentation of brain tissues relies on factors like size, texture, shape, location etc. and their performance while acquiring the image. [3-7]. The extraction of above features makes the further process of classification much faster, easier and also makes the understanding of images better.

Segmentation is a commonly employed methodology for extracting brain tissues like GM, white matter (WM), and cerebrospinal fluid (CSF) from MR image for brain analysis quantitatively [8]. It also helps in detection of diseases like Alzheimer's disease, brain tumor, Parkinson's disease, Hemorrhage etc. However, in the neurological research, segmentation plays a challenging part because of several issues with MR images as noise, intensity inhomogeneity and abnormal tissues showing heterogeneous intensities of signal.

There are several classification methods like K-NN, self-organizing map, support vector machine (SVM), artificial neural network (NN) etc. [8, 9]. We will be discussing NN in the present paper.

Artificial neural network is a computing systems inspired by the biological neural networks, which interconnect the components called as neurons that are programming constructs copying the biological neurons. ANNs consist of multiple layers with each layer having multiple neurons. In striking similarity with the biological neuron which receives, processes, and transmits information through chemical and electrical signals, the ANN neurons are the devices with an activation function, several inputs and a single output [2].

Literature review is given in Section II as related work. The methodology, which is the building block of this study is described in Section III. Under the heading of result analysis, Section IV discusses the experimental result of the methods envisaged in the present study. Finally, conclusion is of the present work is derived and future scope is shown in section in Section V.

## II. Related Research

Historically, numerous MRI classification techniques have been worked on. NN based process was used in along with wavelet transform is applied to extract features from images by Zhang et al [10], for classification of brain MR images as normal and abnormal. The dimensions of features were reduced by principle component analysis (PCA) and finally classification was done using neural network giving 100% accuracy.

In [11] the authors also proposed automatic classification between normal and abnormal images. Two staged decision was made by inclusion of feature extraction using the principal component analysis (PCA) and classification via neuro-fuzzy approach. The performance of neuro-fuzzy classification was based on training performance and classification accuracies. The results of 93.33% accuracy with data set of 35 including 20 training dataset and 15 testing dataset, confirmed the tumor detection potential of neuro fuzzy system.

In [12] classification of brain MRI was done using SVM and ANN classifier. The data set is classified as normal or abnormal in the proposed classification. A data set of 52 images was considered, out of which 46 were abnormal and 6 were normal. Classification accuracy of 94% was achieved with neural network self-organizing maps whereas support vector machine gave an accuracy of 98%. Hence it was found that SVM gave better results as compared to ANN classifier.

The authors in [13] used hybrid technique with three steps. They did feature extraction, dimension reduction, and then further classification. The features extracted via DWT were reduced using principal component analysis. The PCA output was classified in two classifiers- first one based on feed forward back-propagation artificial neural network (FP-ANN) and the second one based on *k*-

nearest neighbor (*k*-NN). A classification accuracy of 97% was obtained with FP-ANN and 98% with *k*-NN, showing *k*-NN having better classification efficiency over the present data set.

The authors in [14] studied Computer aided Diagnostic systems (CAD) for severity assessment of mitral regurgitation (MR). Eight distinct textural features were calculated and used for confirming the MR stages from the regurgitant area. These set of features are gray level difference statistics, spatial gray level difference matrix, statistical feature matrix, neighborhood gray tone difference matrix, law's textures energy measure, Fourier power spectrum and fractal dimension texture analysis. Supervised Classifier (SVM) was used for classification giving 95.65%, 95.65%, and 95.35% classification accuracy in A2C, A4C and PLAX views respectively. Thus the above study indicate that their proposed CAD system can be used for confirmation of mitral regurgitation stage confirmation as mild, moderate or severe.

In [15] author used The minimum redundancy – maximum relevance algorithm to reduce the extracted features. In this method, the mutual information is the parameter to validate the importance of the features, generating a ranking where the features are ordered by its mutual information with the class and with the other features.

In [16] author analyzed the chances of detection of dementia prematurely by the use of no rigid registration of MRI. 81.5% accuracy was found on a data set of 58 images with k-NN classifier was used and was trained on dissimilarity matrix.

The author in [17] used fully automatic segmentation and classification technique using hybrid neural; network process. Different brain tissues were separated on basis of T1, T2 and PD Weighted MR images and volumetric measurement of different intracranial units were done. High intra subject reproducibility was found with a significance of at least $p<0.05$ for grey and white partial volumes, grey matter and white matter respectively. Thus the present study aptly justified the result reproducibility.

For the brain cancer detection and classification computer aided system was used by [18] for lesion detection. In this study the texture extraction was done by Grey Level Co-occurrence Matrix (GLCM) and Neuro fuzzy classifier is used for the recognition of different types of cancers. The system is first trained and then tested.

Classification of healthy and unhealthy brain tissue was done which was further expanded to classification of malignant and benign tumors by [19]. The developed algorithm firstly preprocesses the image and the after image segmentation and feature extraction it leads to classification of images.

## III. Materials and methods:

**(A) Image dataset:** The primary step involving any research wok is the acquisition of image dataset. The brain MR image database constitute of T1-weighted and T2 weighted image. The images are of all three planes, i.e. axial, sagittal, and coronal. Out of 226 images, 88 of them constitute abnormal dataset while 138 are of normal brain MRI. All the images are from same machine (G E Healthcare 1.5 Tesla MR Scanner) and of same resolution.

**(B) Proposed methodology:** This work is basically directed to develop a CAD system constituting of feature extraction and classification algorithms for identification of abnormality on brain MR images thereby aiding the radiologists in decision making process. The stepwise procedure of the methodology is explained in the following figure 1.

### (i) Preprocessing and Skull Stripping:

In this step all the images including normal and abnormal are first resized to 256x256 and then for better training of classifier, skull of brain MR Images is removed using morphological operations.

### (ii) Feature Extraction and Feature Selection:

Two existing feature extraction methods are selected to extract relevant features from selected region of interest. These feature extraction methods are: First order statistics [20], Spatial gray level dependence matrices [21]. The above generated features are then normalized. Feature selection techniques are used for selecting optimal set of features and for reduction of dimensionality. The performance of the system gets lowered dimension of the feature space is pretty more. Although feature selection can be done by varied ways like sequential forward, backward, or floating selections. However, when choice from these mined features is purely based on relevance criterion then many redundant variables also gets selected. In order to get relevance oriented least redundant features, a hybrid approach- "minimum Redundancy Maximum Relevance (mRmR)" procedure is utilized in the current study, proposed by Peng et al. [22].

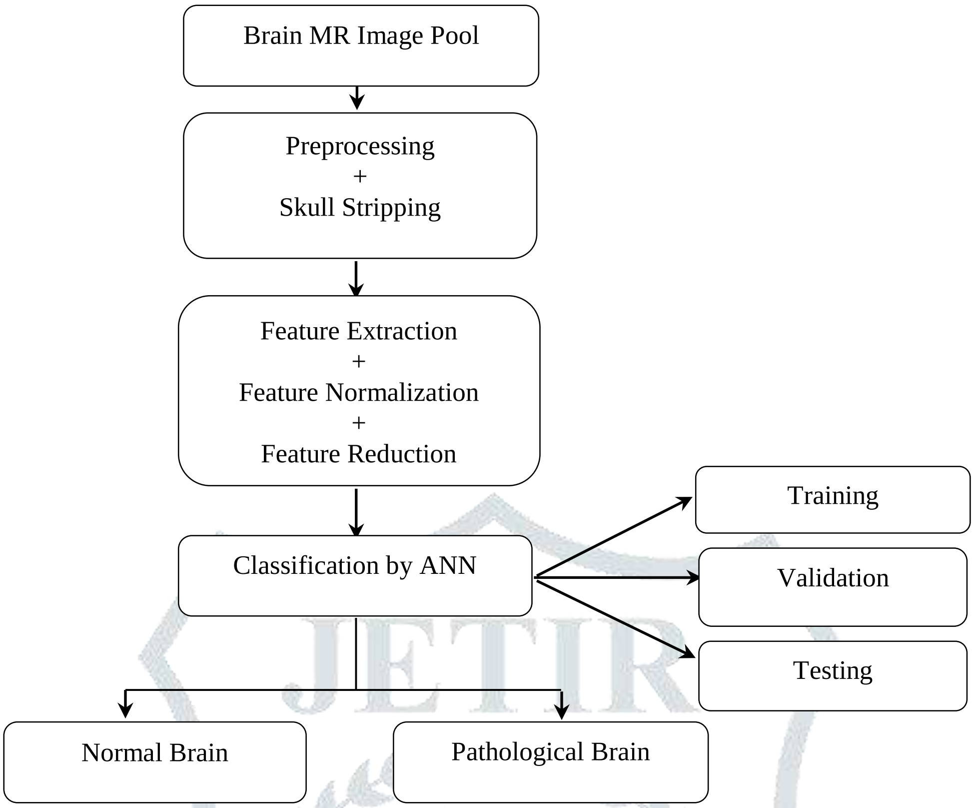


**Figure 1. Schematic of proposed classification approach**

**(iii) Classification:**

Classification is a categorization process of the huge sets of objects that share similar attributes in order to recognize, differentiate, and understand. Artificial Neural Networks (ANN) consisting of multiple nodes, are vaguely inspired from biological neural networks in learning. The input is given to the node or processing elements (PE) which perform some operation thereby passing its output to other neurons generating the node value called activation. Each link is associated with some weight which gets re-calibrated at every training step [23].

ANN can handle much more variability as it has many different coefficients which can be used to optimize the model.

## IV. Result and Discussion:

Texture features of 226 total number of MR brain images is calculated by FOS and SGLDM approaches. 31 features in totality are calculated for each image and these are reduced to 8 by using mRMR feature selection method. Figure 2 depicts T1 and T2-weighted MR image data of abnormal and normal brain in axial, sagittal and coronal planes. Each image taken is of 256 x256 resolution. The performance of this method is quantified in the terms of confusion matrix, accuracy, precision, recall, sensitivity and specificity. Above measures are calculated by the given formulas.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$F-measure = \frac{2*Precision*Recall}{Precision+Recall} \tag{4}$$

The true positive, false positive, true negative and false negative are assigned acronym as TP, TN, FP, FN respectively in equation 1 to 4.

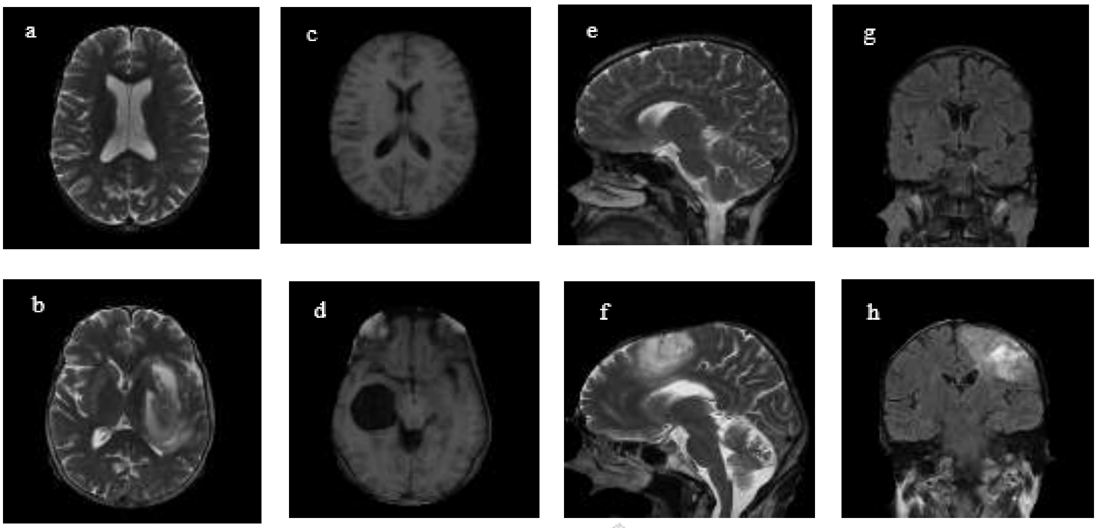


**Figure 2. Abnormal and Normal Brain MR Images-** (a, b) Axial T1 weighted normal and abnormal, (c, d) Axial T2 weighted normal and abnormal, (e, f) Sagittal T1 weighted normal and abnormal, (g, h) Coronal T2 weighted normal and abnormal images respectively

Table 1 shows the classification result of the proposed method for different cross-validation folds. 15 fold NN gave the highest accuracy in classification.

**Table 1. Classification approach for different cross- validation folds**

| Number of folds | Class | Precision | Recall | F-Measure | Accuracy |
|---|---|---|---|---|---|
| **5** | P | 0.927 | 0.864 | 0.894 | 92% |
| | N | 0.917 | 0.957 | 0.936 | |
| **10** | P | 0.964 | 0.909 | 0.936 | 95.1% |
| | N | 0.944 | 0.978 | 0.961 | |
| **15** | P | 1 | 0.909 | 0.952 | 96.5 % |
| | N | 0.945 | 1 | 0.972 | |

## V. Conclusion and future scope:

Medical images play important role in diagnosis of diseases harming human brain. Even though MRI images are of high quality delineating internal structures and soft tissues, there classification is somewhat a cumbersome task. Classification through any CAD model is of great help to radiologist and researchers. ANN are such supervised pragmatic model which are used for class prediction and back propagation neural network (BPNN) has been proved more effective than other schemes in ANN. The proposed model yields its highest accuracy of 96.5%. Further work will include inclusion of other methods for feature extraction and feature selection. Also this study can be extended to classify different classes of particular lesion rather than just differentiating between normal and abnormal brain.

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