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Abnormal Tumor Classification of MR Brain Images Using Deep Neural Networks

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ABSTRACT

A cell in the brain is a smallest unit of tissue and its abnormal growth leads to brain tumor. This paper presents an effective way of classifying the abnormal MR brain images using customized 10-layer fully connected deep neural network. The process starts with removing of skull region from the brain image using image processing methods and later include pseudo color transformation of the axial T1-weighted MR brain images where the gray scale images are converted into "Lab" color domain. Multiple regions of the brain are labeled which are been trained for the custom designed deep neural network. The classification accuracy of the proposed network attained 98% which is superior than earlier SVM and HMM classifier methods.

Keywords:
Brain classification, abnormality detection, deep networks, pseudo color transform

1.Introduction

A malicious or abnormal region in the brain occurs when abnormal cells unite together within the brain. There are multiple ways to diagnose these abnormal regions but one of the best way is MR imaging.MR (Magnetic Resonance) Imaging has the advantage of having very high spatial resolution and is very adept at morphological imaging and functional imaging [1]. MR imaging technique analyses the brain on the basis of density of water particles present in soft tissue which is greater when compared with bone tissues [2].

With the help of MR imaging the radiologist could able to visualize the anatomy of brain structure visually without performing any physical surgery. But, this manual inspection of MR images may lead to wrong diagnose if the radiologist is not well experienced, hence it is recommended to adopt fully automatic methods [3].

The method proposed in the current work aims to classify the healthy and non –healthy brain images. Detection of brain region and classification of abnormal regions is one of the crucial task than detection of any image object in any image.

Table 1: MR brain imaging types and the slice thickness

Anatomical - Plane	**Weighting**	**Contrast**	**Slice thickness or spacing**
Sagittal	T1-weighted	-	5mm/6mm
Axial	T1-weighted	-	4mm/4mm
Axial	T2-weighted	-	5mm/4mm

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Sagittal	T2-weighted-Flair	-	5mm/6mm
Axial	T1-weighted	Gadolinium	4mm/4mm
Sagittal	T1-weighted	Gadolinium	5mm/6mm

Above table 1 depicts the MR brain imaging protocol of acquiring the brain image and its respective slice thickness.

The shape of the objects usually relies on pattern recognition. In the case of brain tumor whose shape often varies may not be relied on this pattern recognition hence, other properties are to be employed. So a prior knowledge base is used to detect whether the brain image is healthy or not. One of such probabilistic is the availability of tissue locations based on brain atlas [4]. In this analysis general properties of healthy and non-healthy brain are used as prior knowledge base. The alternate way of analyzing the details of the brain is to use the symmetry of the brain region where the abnormal regions are detected by the breakage of this symmetry [5][6].

In this paper an automated analysis of the MR brain images is discussed where the entire paper in categorized into sub section namely brain belonging to normal subjects and other brain region belonging to abnormal or pathological subjects. So in order to extract the desired features from each image automated tools are to be employed. The paper is organized as follows, in section 1 the basic introductory content related to brain anatomy and classification methods were discussed. In section 2, a brief literature about the related works performed earlier by the researchers were discussed. Section 3, discusses about the proposed approach presenting the experimental results attained in section 4.

2.Related Work

The process of automatic classification of abnormal regions was developed using computer aided diagnosis (CAD) systems. This CAD could able to provide more appropriate and accurate results than earlier brain detection approaches. To accomplish this several methods and approaches were given by several researchers, some of them which are related to the current work are discussed in this section.

Roslan et al., [7], Somasundaram and Kalavathi [8] [9] developed a new fully automatic skull stripping algorithm for T1, T2-weighted MR brain images for segmenting the brain from other non-brain tissues using Chan-Veese active contour method using two stage processes. First they extracted the brain in the middle slice by drawing initial contour inside the rough brain portion to propagate the active contour. Brain extraction in the remaining slices was performed in the second phase by using simplified geometric similarities of the adjacent slice.

Somasundaram and Kalavathi [10] have proposed automatic brain segmentation named as Multi-Seeded region growing (BSMRG). This algorithm aims to extract the brain region from T1 and T2 weighted MR human brain images in all three view of orientations. This method mainly shows 2 stages of processing; the first process includes volume calculation in middle slice of MR

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image. Later in second process the volumetric slices were segmented. In both the stages, pre-processing, brain region extraction and seed point selection were employed in BSMRG.

In [11] Abinaya et.al have developed an intelligent system to segment brain with particle swarm optimization method and applied the developed concept on 50 real time MRI dataset. Sucharitha and others [12] has reformulated the Fuzzy Local Information C-means with conventional clustering. Here they have considered both spatial and intensity level information which was later replaced by coefficient of variation in fuzzy manner. Later these processed images are segmented into White matter, White matter and CSF regions of brains.

Elazab et.al [13] proposed Regularized Kernel based FCM approach that mainly intends to preserve the image edge details in MRI brain image. This method includes three forms of algorithms the local average grey scale which is replaced by average filter, median filter and weighted images. In this analysis the distance calculation which earlier to be a conventional Euclidean distance is replaced by Gaussian radial basis kernel function for higher accuracy.

A combination of Bayesian algorithm with adaptive mean shift algorithm provides a prior spatial probability which was proposed by Mahmood and Chodorowski [14] for segmenting synthetic, real 20 volumes and 18 volumes of T1-w MR images. An efficient improved KM algorithm developed by Liu and Guo [15] uses traditional KM for simulated brain images of T1-w with different noise levels. Hayat and Ahmed [16] proposed an unsupervised way of segmenting the tissues in MR brain images, this is obtained with the integration of Bayesian adaptive mean shift algorithm with conventional FCM clustering.

3. Background

In our earlier work [21], the abnormality classification is performed with machine learning classifiers like support Vector machines (SVM), Hidden Markov Models (HMM). At the beginning of the approach the images are segmented using super pixel segmentation where the image is partitioned into multiple unequal regions of similar content [24]. Later statistical features are extracted for each segmented portion. Parameters such as Contrast, Homogeneity, Energy, Skewness, Kurtosis, and Inverse difference moment were calculated. mathematically represented as a function of f(i,j,d,ϴ) where the pixel pair is separated by a distance of ‘d’ and is oriented at ‘ϴ’. This is a square matrix which has the value of the largest pixel in the image.

$$\mathrm{Con} = \sum_{i=1} \sum_{j=1} (i-j)^2 p(i,j) \quad (1)$$

$$\mathrm{En} = \sum_{i=1} \sum_{j=1} p(i,j)^2 \quad (2)$$

$$\mathrm{Sk} = \frac{1}{\sigma^3} \sum_{i=1} \sum_{j=1} (f(i,j)-\mu)^3 \quad (3)$$

$$\mathrm{Kr} = \frac{1}{\sigma^4} \sum_{i=1} \sum_{j=1} (f(i,j)-\mu)^4 \quad (4)$$

In the above equations i,j represents the dimensions of the matrix , sigma is the standard deviation , and mu is the mean. These features are normalized and fed to the classifier for training.

SVMs belong to the class of maximum margin classifiers. They perform pattern recognition between two classes by finding a decision surface that has a maximum distance to the closest

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points in the training set, which are termed support vectors [25]. Unlike other classifiers, SVMs control their generalization ability by minimizing their error rate on the training set and their capacity.

Let a training set of points be $x_i \in R^n, i = 1,2 \ldots . N$ where each point of x_i belongs to one of two classes identified by the label $y_i \in \{-1,1\}$. Assuming linearly separable data, the goal of maximum margin classification is to separate the two classes by a hyperplane such that the distance to the support vectors is maximized. This hyperplane is called the optimal separating hyperplane (OSH) which has the form

$$f(x) = \sum_{i=1} \alpha_i y_i\, x_i . x + b \qquad (5)$$

The terms α_i and 'b' are the solutions of the quadratic programming where the classification of new data point 'x' is performed by computing the sign of the right side of the above equation (5) . Subsequently, the following equation will be used to perform multi-class classification

$$d(x) = \frac{\sum_{i=1} \alpha_i y_i x_i . x + b}{|| \sum_{i=1} \alpha_i y_i x_i . x ||} \qquad (6)$$

The sign of 'd' is the classification result for 'x', and |d| is the distance from 'x' to the hyperplane. Intuitively, the farther away a point is from the decision surface, i.e. the larger |d|, the more reliable the classification result.

4. Proposed Methodology

To facilitate accurate analysis of brain structures, extradite of non-brain regions has to be performed. In this work, this brain extraction and removal of non-brain regions is performed using morphological operation which slightly related to [9]. Later, a pseudo color transformation is applied to transform the gray scale images such that each region of the brain can be easily distinguished from one other. A customized deep network is designed and trained for the classification of the abnormal images. The block diagram of the proposed approach is depicted below in figure 1.

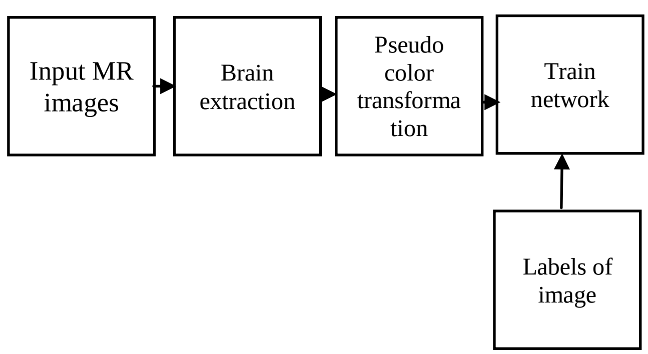

Figure 1 (a): The training process of the network

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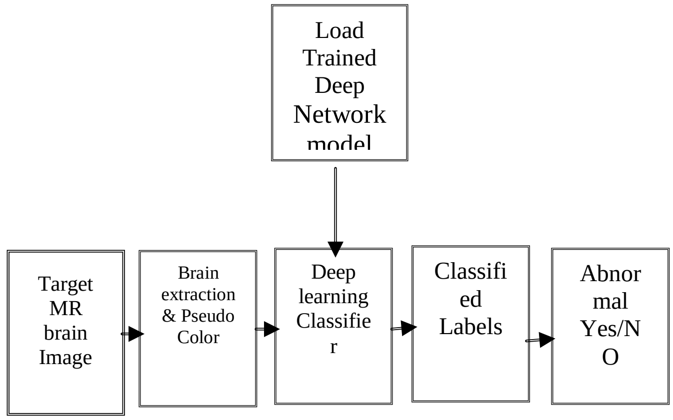

Figure 1(b): Classification process with network

4.1 Brain Extraction Process

Given an input MR brain image which do consist of unwanted skull region. It was observed by earlier researchers [17] that removal skull regions increase the segmentation efficiency. In order to facilitate this a sequence of morphological operation of octagon structuring element were applied on the input image resulting in a binary patch that replicates the brain region.

Let I(x,y) be the input image which is subjected to morphological erosion process the structuring element of B(x,y) , then the resultant image Ie(x,y) is given as

$$\mathrm{Ie}(x,y) = \mathrm{I}(x,y)\Theta \mathrm{B}(x,y) \qquad (7)$$

Later this eroded image is subjected for binary thresholding where the thresholded image is given as

$$\mathrm{I_t}(x,y) = \begin{cases} 1 & \text{if } \mathrm{I_e}(x,y) \neq 0 \\ 0 & \text{otherwise} \end{cases} \qquad (8)$$

This thresholded image is further processed with binary dilation process with a structuring element of $B_1(x,y)$ to attain the resultant outer skulled portioned removed image.

$$\mathrm{I_r}(x,y) = \mathrm{I_t}(x,y) \oplus \mathrm{B1}(x,y) \qquad (9)$$

Thus, we attain a skull removed MR brain image which is suitable for abnormal region extraction and classification.

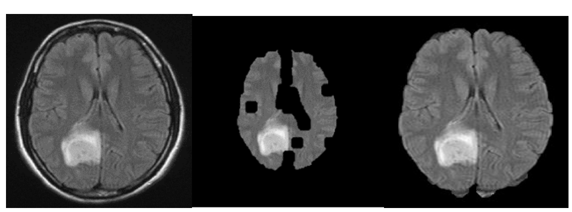

Figure 2: (a) Original Image (b) After eroded process (c) Resultant final extracted brain region

Later, these extracted images are transformed into Pseudo color transform. In this work “LAB” color transformation as used in [18]. When the input image is in true color domain then the following are the mathematical equation that are involved in converting into LAB color transform.

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$$X = 0.4303R + 0.3416G + 0.178B \quad (10a)$$
$$Y = 0.2219R + 0.7068G + 0.071B \quad (10b)$$
$$Z = 0.0202R + 0.129G + 0.931B \quad (10c)$$
$$L = 116\left(h\left(\frac{Y}{Y_s}\right)\right) - 16 \quad (11a)$$
$$a = 500\left(h\left(\frac{X}{X_s}\right)\right) - h\left(\frac{Y}{Y_s}\right) \quad (11b)$$
$$b = 200\left(h\left(\frac{Y}{Y_s}\right)\right) - h\left(\frac{Z}{Z_s}\right) \quad (11c)$$

In the above equation the transform function h(.) is represented as

$$h(q) = \begin{cases} \sqrt[3]{q} & q > 0.008 \\ 7.87q + \frac{16}{116} & q \leq 0.008 \end{cases} \quad (12)$$

And the terms X_s, Y_s, andZ_s are the standard stimulus coefficients of the respective vectors.

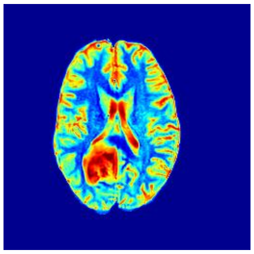

Figure 3: Pseudo Color transformed Image

4.2 Developed Deep Network for classification

The problems associated with machine learning can be best solved when represented structurally. Automated Learning through the representation of the real-world data is the fundamental aspect of Deep Learning. If an image contains multiple objects and as pacific object to get detected it is tough to write a specific program. One needs to be sure of the target location in the image to find the intended object located in a specific region. Deep Learning inspired by Neural Networks comes to the rescue of this kind of learning. However, Neural Networks have been researched and has been active in the industry for over the past six decades. Advancements in hardware and machine learning libraries paved the way to solve complex problems. The ability to introduce multiple hidden layers in Neural Networks opens up, a tremendous opportunity to learn the data deeply. Hence Deep Learning techniques can learn the representation of the data and, surprisingly optimize the learning among the neurons using back propagation techniques with Convolution Neural Networks (CONVNETS).

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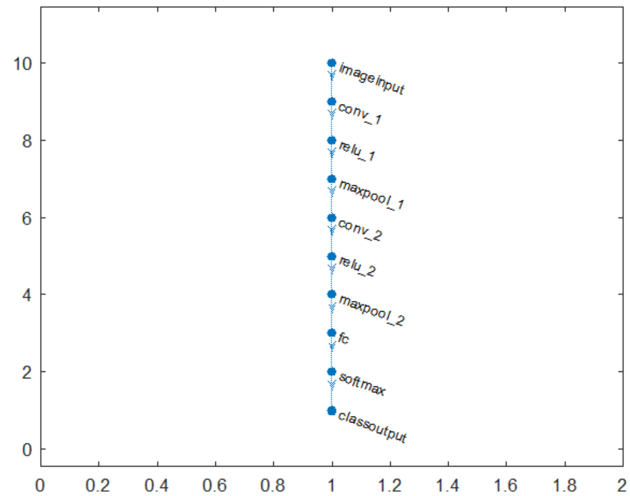

Figure 5: Layer connectivity of the proposed architecture

In this work a 10 layered architecture is developed to classify the abnormality of the brain images. The input size of the image is 256x256 true color image proceeding to a convolutional layer with 7x7 filter size and 20 filters. This layer is processed to ReLu layer followed by max-pooling where a down sampling of factor 2 is performed.

These layers are concatenated with the same type of layers which are then forwarded to fully connected and soft max output layers. While training a label ‘1’ is given for the abnormal image and label ‘0’ is given for normal images, so at the output layer the outcome will be a class number stating to which class the particular image belongs to.

Input image size: 256x256
2-D convolutional layer: 7x7x3 (20) stride :1+ReLu
Max-Pooling layer-1:2x2 with stride:2
2-D convolutional layer: 7x7x20, stride:1+ReLu
Max-Pooling layer-2:2x2 with stride:2
Fully Connected: 2
Softmax Output: Cross Entropy

Table 2: Proposed design details of the Deep Network model

5. Experimental Results

To evaluate the performance of the proposed work, 80 abnormal and 80 normal images collected from [19] and [20]. These images are preprocessed, pseudo color translated and brain extraction process as stated in section 3 is performed. This work is compared against with our earlier method with SVM [21]. The concept of SVM can be referred from [22]

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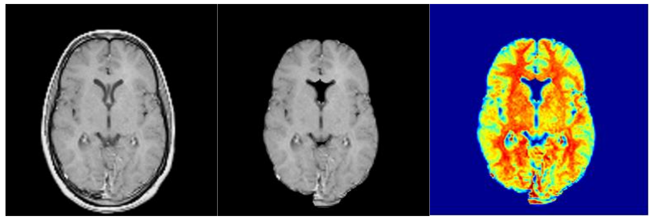

Figure 6: (a) Original MR image (b) Extracted Brain region (c) Pseudo Color transformed image

Algorithm with SVM. HMM classifier

- Create a dataset of Normal and Abnormal Images
- Read an image and remove the skull using brain extraction process stated in section 4.1
- Segment the image with SLIC algorithm [24] into multiple segments
- Calculate features mentioned in section 3 for each segmented portion and construct a feature vector and its corresponding label of {1, -1} representing the normal and abnormal features
- Train the classifier with Linear type of kernel [26] and save the model.
- Repeat the above 2 to 4 steps for query image and extract the classified label from the classifier

Algorithm with Deep Learning

- Create a dataset of Normal and Abnormal Images
- Read an image and remove the skull using brain extraction process stated in section 4.1
- Perform 'LAB' transformation and store the resultant images in separate directory
- Construct a 7-layer deep network as mentioned in table 2 feeding it with the images of size 256x256
- The images are partitioned into several 3x3 patches which are convolved with 3x3 mask in the convolutional layer and then processed to the bottom layers
- While training the network is fed with the labeling of the images with [0 1] representing the abnormal and normal
- For a query image repeat the 2 and 3 steps and then feed the image matrix to the trained model which will be classified as either 0 or 1 stating whether it is abnormal or normal

The classification detection accuracy of both the classifiying approaches are tabulated in table 3 and figure 7, 8.

Table 3: Tumor detection performance

Test	**Tumor Present**	**Tumor Absent**
Test Positive	98.8%	1.2%
Test Negative	1.5%	98.5%

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Table 4: Classified Output Vs Ground Truth

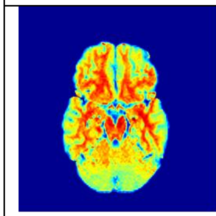
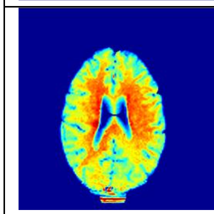
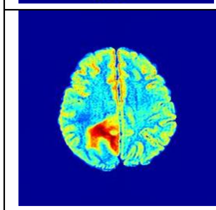
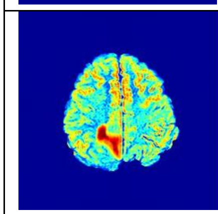
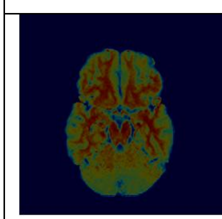
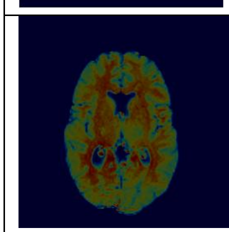
Image	Classified Output	Ground Truth
	Normal	Normal
	Normal	Normal
	Abnormal	Abnormal
	Abnormal	Abnormal

Table 5: Classified Output when illumination is decreased by 70% Vs Ground Truth

Image	Classified Output	Ground Truth
	Abnormal	Normal
	Normal	Abnormal

It can be observed from the above performance analysis that though there is a change in the illumination of the input image the network could able to detect accurately, this shows the robustness of the proposed network design to change in illumination and there can be useful in multiple environments. The method also compared against the classifiers mentioned in [21] and

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found that the network could able to attain ~10% superior level of accuracy which is observed to be good achievement for the current work.

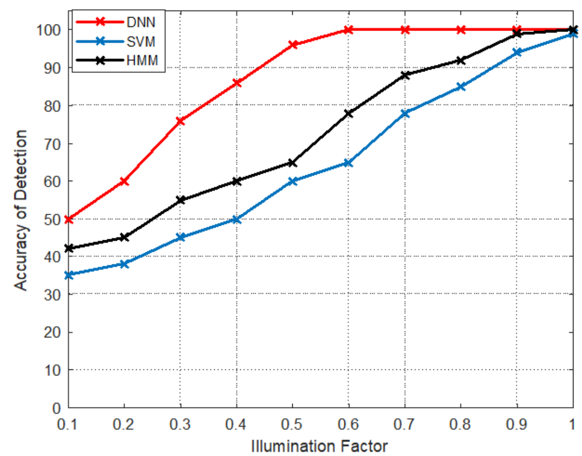
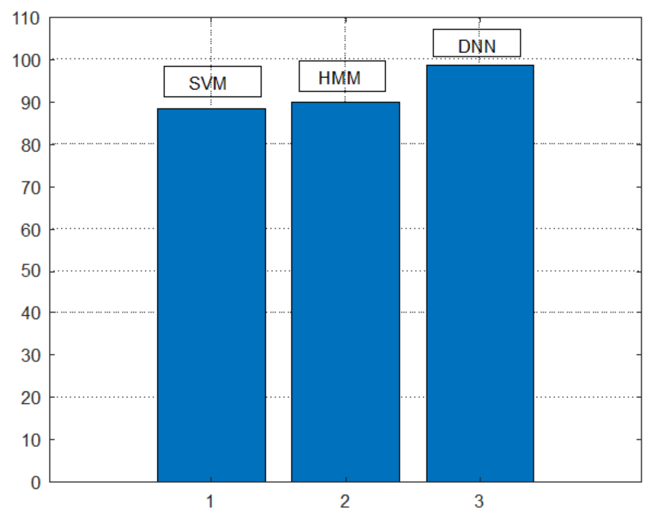


Figure 7: Performance analysis of proposed approach under varying illumination and its comparison with SVM, HMM



y-axis : Average Accuracy of classification
x-axis : Classifier Type

Figure 8: Performance analysis of the proposed approach with earlier [21] work

5. Conclusions

The paper proposes an effective and simple approach of detecting the abnormality in MR brain images. The objective of the work is to classify the abnormal mages which was effectively achieved with developed network. The initial part of the work concentrates on extracting the brain regions and trains them with customized developed network. The second part of the work focuses on validating the network with multiple images under different illumination changes. From the experiments conducted it was observed that the method could able to retain an average detection accuracy of 98.8% which is far superior than earlier feature based classifier approaches.

However, this method proves to be sustainable for the changes in the illumination upto 60% decrement in the illumination yield cent percent classification output beyond which it could able to attain only 80% of the classification accuracy. The method is compared against the traditional classifier outputs that were used in our earlier work and observed that this approach is yielding 8~10% more accuracy than those methods.

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