

## Brain Tumor Detection using DNN Algorithm

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**Abstract:** Machine Learning has provided the way for scientists to achieve great technical feats. An algorithm that achieves considerable results in detection of image and segmentation is known as Deep Neural Network. In a venture to augment and sharpen these techniques, we propose a DNN structure which utilizes stacked auto-encoders. Biopsies are used to classify brain tumors and are not normally performed prior to conclusive brain surgery. The advancement of machine learning will help in assisting the radiologists in tumor diagnostics without the use of invasive procedures. We leverage the speed and human-centric benefits of it to improve medical imaging facilities. With improved training speeds and accuracy, machine learning can open new doors for medical workers. It will simplify the process of understanding the human brain and will save a massive time bypassing the computational burden of scanning through medical images manually.

**Keywords:** Deep neural networks (DNN), Convolutional neural network, Auto-encoders, Brain-tumors, Machine learning

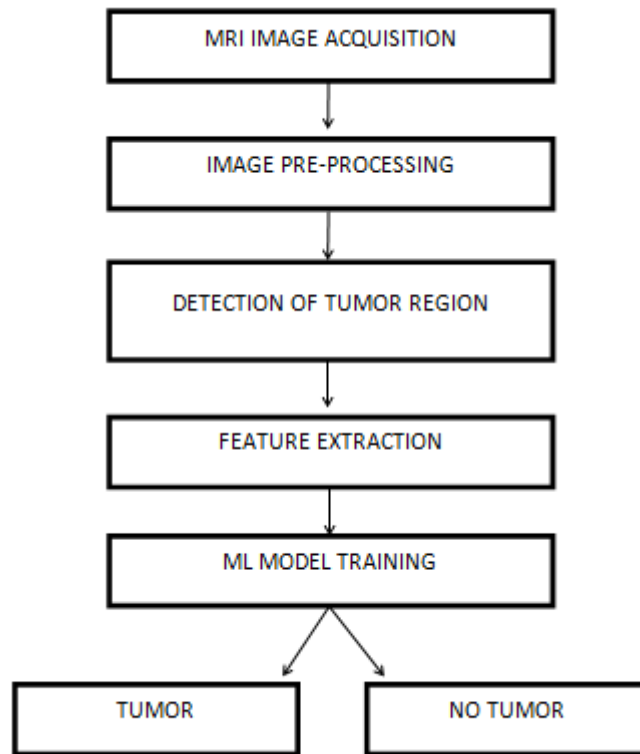
### 1. Introduction

Brain tumors are a life-threatening disease for humans. Brain tumors are uncontrollable growths of tissue or cells in or around the brain. Cells in our bodies usually develop, become weakened, and die, but this process does not occur in certain people. The new cells do not divide and the old cells remain in the body, causing the growth of more cells into a mass of tissues known as a tumor. A brain tumor is thought to be a set of rare cells framed in the brain. The brain tumor can occur at any time during one's life, but they are not all the same. A brain tumor is a mass of abnormal cells in our brain that can be divided into two types: malignant (non-destructive) and benign (destructive / harmful). Although the function of the tumor has not yet been determined, some of the reasons may serve as the basis for a brain tumor. The primary motivation for a brain tumor is ancestry. Family characteristics are responsible for about 80% of the chances of developing a brain tumor. Age, compound exposure, family ancestry, radiation exposure, and ethnicity are all risk factors for brain tumors.

In [4] "Computer Aided System for Brain Tumor Detection and Segmentation" the methodology used is enhancing the MR image and segmentation of tumor using global thresholding. Using morphological operations and by applying window technique the False segmented pixels are removed. The proposed method is invariant in terms of size and shape of brain tumor. [5] In "Brain Tumor Detection Using Deep Neural Network and Machine Learning Algorithm" paper, an entirely different method is used based on the combination of CNN for tumor detection and feature extraction algorithm from brain images. [6] In "Brain Tumor Detection and Classification Using Deep Learning Classifier on MRI Images" paper, classification of tumors is done by multiple kernel-based probabilistic clustering and also by using deep learning classifier. [7] In "Binarized Neural Networks" a new method of BNNs is introduced, which binarizes the deep neural networks and can lead to dramatic improvements in consumption of power and speed. [8] In "Brain Tumor Detection based on Machine Learning Algorithms" paper proposes a work on brain tumor detection system based on machine learning algorithms. The texture based features are extracted using Gray Level Co-occurrence Matrix (GLCM) [8]

### 2. Proposed System

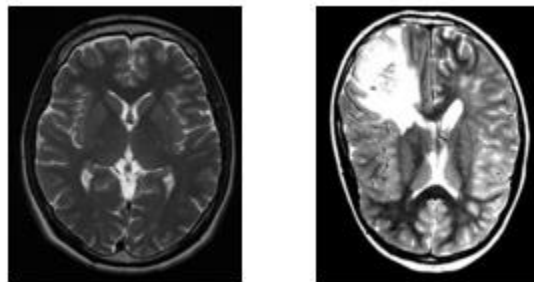
The proposed system defines the processes of tumor detection from the MRI images. They are described in the figure below.



**Figure 1.** Proposed system block diagram

### 2.1.Choice of brain images

Currently, various imaging methods, such as X-Ray, CT scan, and Magnetic Resonance Imaging (MRI), are available through various techniques. The X-Ray provides picture evidence about the life structures and the whole synthesis of the brain or skull. Data containing the blood supply within the brain can be obtained with the aid of an MRI scan. As a consequence, it is fair to assume that MRI procedures have become an effective method for detecting oddity, monitoring the course of the disease, and making decisions.



**Figure 2.** Sample input image of MRI scan

We used the BraTS dataset which uses the state of the art methods for acquiring multimodal MRI scans converted NifTI file format into trainable JPEG file. The dataset used was acquired from <https://www.med.upenn.edu/cbica/brats2020/data.html/>.

### 2.2.Image preprocessing

The aim of the pre-processing stage is to optimise image data by suppressing unnecessary distortions and improving certain essential image features for subsequent processing. Image enhancement is a pre-processing method used to transform an initial image into a more desirable version.

The following steps are followed in the pre-processing stage:

The original image is paired with the sharpened images for further enhancement.

When MRI scanned images are stored in a database, they are converted to grey scale image sizes of 255 x 255

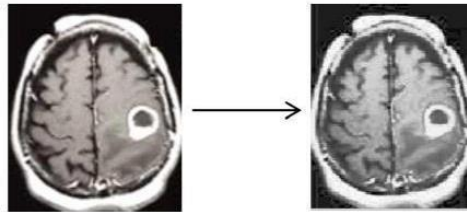
Since these photographs have been processed to eliminate noise, the visual quality of the noise images has been affected.

The high pass filter for edge detection and sharpening is responsible for the image's high resolution and lack of noise.

The two pre-processing methods used in the proposed work are:

### 2.1.1.Histogram equalization

Histogram equalization is used to enhance the contrast of a grey scaled image by mapping new pixel values to the histogram. It is the method of extending the dynamic spectrum of an image's histogram. Histogram balancing allocates the force estimations to pixels in the information Image such that the yield Image has a uniform dispersion of forces and increases image separation.



Figur 3. Histogram equalized image

### 2.1.2.Binarization

Because of the noise in the images, Auto encoders are not able to recognize the images. To avoid the background noise produced in the images we use Binarization technique. A colour image is made up of three channels (R, G, and B), each of which has a value ranging from 0 to 255. Converting greyscale images to black and white (0 to 1) is one of binarization's most important features. Binarization often makes the contours of different objects in the picture smoother and simpler. The learning of the model is improved by this function extraction.

$$(x,y) = \begin{cases} 1 & f(x,y) \geq T \\ 0 & f(x,y) \leq T \end{cases} \quad (1)$$

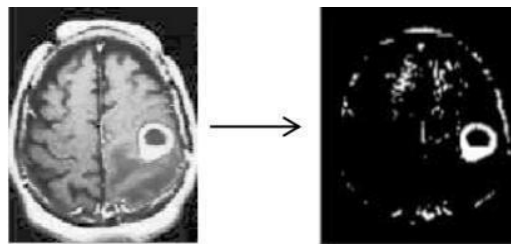


Figure 4. Binarized image formed from grey scale

### 2.2.3 Feature extraction

This investigation focused on two viable GLCM surface features: homogeneity and vitality. The homogeneity quantifies the closeness of the dim level framework's circulation highlights. Furthermore, the Histogram of Oriented Gradients (HOG) descriptor is used to prepare the sectioned image, and PC type is used to remove the ideal element esteems.

#### 2.2.3.1 GLCM

The Gray Level Co-Occurrence Matrix (GLCM) technique is a histogram of co-occurring grey scale values at a given offset over an image. The GLCM functions calculate how often the pixels pairs with unique values and in a given spatial relationship appear in an image create a GLCM, and then extract statistical measures from this matrix to describe the texture of an image.texture classification using GLCMs.

#### 2.2.3.2 HOG

Histogram of Oriented Gradients (HOG) is an element descriptor that is commonly used to distinguish highlights from image data. It is commonly used in computer vision projects for object detection. Finally, the HOG will generate a Histogram for each of these areas separately.

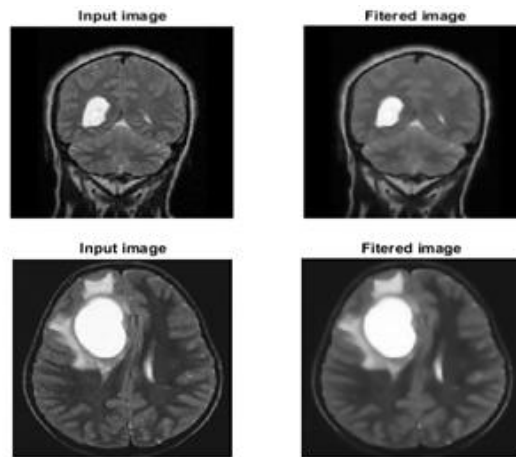


Figure 5, 6. Input images of MRI brain scans and filtered versions

2.2.4 Detection of tumor

to detect the region of brain tumor through machine learning we use DNN with stacked auto encoders for the Brain Tumor knowledge characterization, which enhances all evaluation measures of the diagnosis. As previously mentioned, the DNN classifier for the Brain Tumor dataset is designed using stacked auto encoders and the softmax layer. Two layers of auto encoders were layered on top of each other to create the DNN.

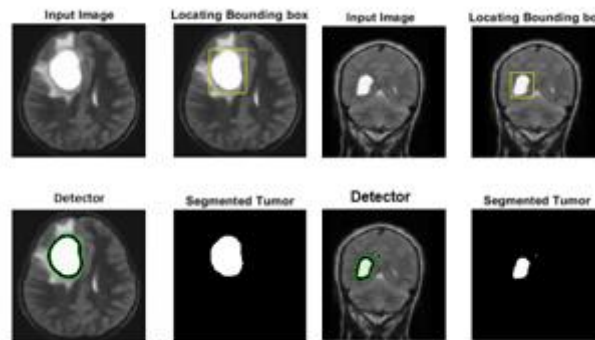


Figure 7, 8. Locating the tumor and detecting it using DNN

2.2.4.1 Autoencoder

Autoencoder has found itself major uses in medical imaging and classification as it is used for image de-noising and super resolution. It is a neural network that maps its input layer to the output through a hidden layer that is used for dimensionality reduction.

The feed forward neural system, the input layer, the hidden layer, and the output layer form the three layers of an autoencoder. The input and output layers of auto encoders have the same number of neurons, allowing them to self-train to replicate the provided input. The Auto encoder’s secret layer converts the information vector from the input layer into text. To create an autoencoder, the total number of secret layer neurons is increased or decreased in the same way that the input layer neurons are increased or decreased. During the planning stage, the input vector is mapped to the highlights. In any case, the autoencoder attempts to convert the information vector into highlights that can be used in the information characterization process.

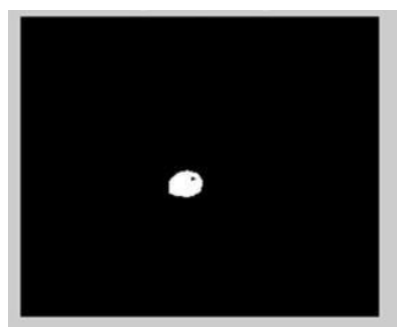


Figure 9. Detected output

**2.2.4.2 Stacked autoencoders**

Stacked autoencoder is a neural network consisting of a few layers of sparse auto encoders, with the yield of each hidden layer compared with the output of the successive hidden layer.

The stacked autoencoder consists of three stages:

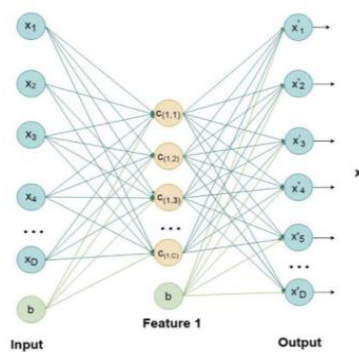
To train the autoencoder with input data and to obtain the scholarly data.

The information gathered from the previous layer is used as a contribution for the next layer, and this process is repeated until the planning is completed.

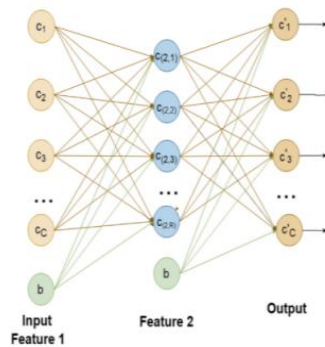
After all of the hidden layers have been prepared, use the back propagation calculation to restrict the cost potential, and loads are refreshed with the preparation set to achieve tweaking.

**2.2.4.3 Softmax layer**

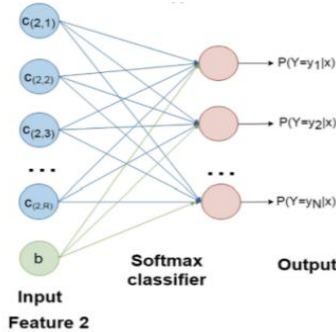
It is a multiple class classification method that is often used as the last step of the activation function in neural network. The classifier evaluates the likelihood of each class based on the information organised in the multiclass classifier problem. As a result, the entire probability distribution of the output classes would be normalized to one. When all the layers in the system are ready, fine tuning is performed and then it is calibrated.



**Figure 10.** Network autoencoder 1



**Figure 11.** Network autoencoder 2



**Figure 12.** Softmax classifier

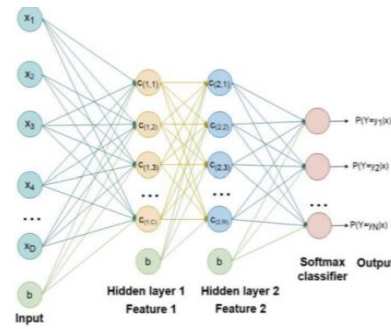


Figure 13. Complete DNN Structure

2.2.5 Evaluation measurements

Classification of Accuracy is considered to be a final metric for examining the results delivered by a few techniques used in the dataset in the writing. The condition will provide classification accuracy:

$$evaluate(n) = \begin{cases} 1 & \text{if } classify(n) = cn \\ 0 & \text{else} \end{cases}$$

Where,

N denotes the dataset to be sorted. Accuracy, Specificity, Precision, Recall, and F1-score are the four metrics used to evaluate a technique based on the parameters of the confusion matrix.

There are four main terms:

True Positives: Situations where we predicted YES and the output was also YES.

True Negatives: Situations where expected NO and the output was also NO.

False Positives: Situations where we expected a YES but received a NO.

False Negatives: Circumstances where we expected NO but instead got YES.

These measurements are determined by the conditions mentioned below.

$$Accuracy = \frac{TP + TN}{TN + TP + FP + FN} (\%)$$

$$Specificity = \frac{TN}{TN + FP} (\%)$$

$$Precision = \frac{TP}{TP + FP} (\%)$$

$$Recall = \frac{TP}{TP + FN} (\%)$$

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall} (\%)$$

Classification Accuracy is the ratio of number of accurate predictions to the total number of input samples.

$$Accuracy = \frac{\sum_{i=0}^{|N|} evaluate(i)}{|N|}$$

$$Accuracy = \frac{Number\ of\ Correct\ predictions}{Total\ number\ of\ predictions\ made:}$$

3.Results

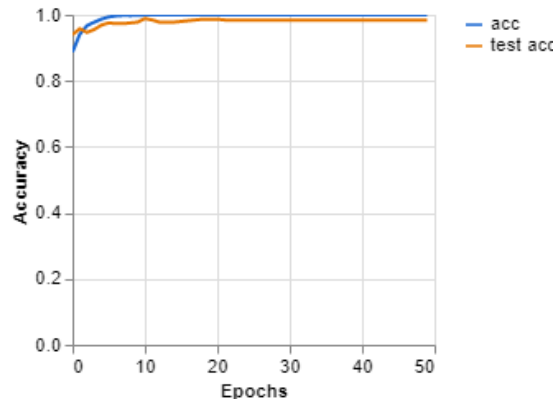


Figure 14. Obtained accuracy results

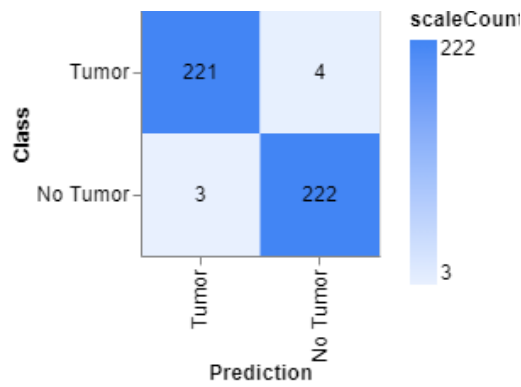


Figure 15. Obtained loss results

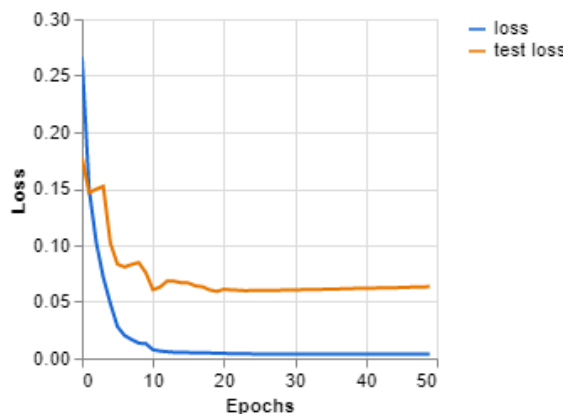


Figure 16. Confused matrix – testing data

Table 1. Comparison of evaluation metrics

Evaluation Metrics	DNN	DNN with fine tuning (50 epochs)
Accuracy	93.2	95.3
Specificity	82.5	87.8
Precision	90.1	93.7
Recall	87.6	92.2
F1- Score	91.3	94.6

#### 4..Conclusion

In the field of medicine, brain image segmentation is critical in surgical preparation and treatment planning. We proposed a method for brain MR image segmentation for tumor location detection using the stacked auto-encoders followed by DNN in this paper. Our model assists in anticipating a patient's Brain Tumor with greater exactness, particularity, precision, and analysis, all of which are important in the restorative world.

#### 5.Future Work

In the future, the proposed study could be expanded to include various types of modalities for detecting tumors, as well as the optimization method used to improve classification accuracy.

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