



CLASSIFICATION OF BRAIN TUMOR USING CNN

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ABSTRACT

Brain tumor detection is one of the main tasks in the medical field till now. Earlier they used pneumoencephalography and cerebral angiography which had a draw-back and the drawback is overcome by CT and MRI scan techniques with the help of surgeons to providing a higher quality result in image processing. It is difficulty in distinguishing between brain tumor tissue and normal tissue because it was similar in color. Hence Brain tumor must be analyzed more precisely in order to cure it by using this image processing. The Proposed method consist total three steps. It mainly emphasizes on proper construction of a more precise, four class brain tumor classifiers from MRI images and pays attention to remove these limitations effectively using a hybrid solution. Firstly, images are pre-processed by resizing, cropping and contrast enhancement. Secondly, feature extraction is done using Local Binary Patterns (LBP) and Histogram Oriented Gradients (HOG). Finally, Convolutional Neural Network is used for classification of Normal, Glioma, Meningioma and Pituitary type tumors in an efficient way. Here the comparison of Local Binary Pattern and Histogram Oriented Gradient features extraction techniques is done while classification. An effective training function is used for proposed neural network construction. This proposed method provides High accuracy of detection. This improved result is comparatively better than other existing detection techniques. The basic reasons for getting magnificent results are the utilization of perfect pre-processing steps and effective training function.

Keywords: *Pneumoencephalography, cerebral angiography, Local Binary Patterns, Histogram Oriented Gradients, Glioma, Meningioma and Pituitary*

I. INTRODUCTION

MRI is an advanced medical imaging technique providing rich information about the human soft-tissue anatomy. It is mostly used in radiology in order to visualize the structure and function of the human body. Today, one of the major causes for the increase in fatality among children and adults is brain tumor.

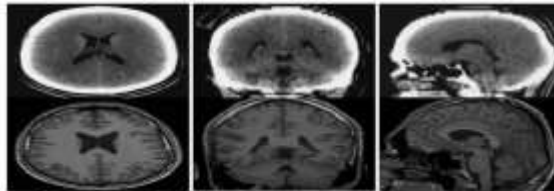


Fig 1. Brain Analysis

Tumors that can directly destroy all healthy brain cells. It can also indirectly damage healthy cells by crowding other parts of the brain and causing inflammation, brain swelling and pressure within the skull. Normally, the benefit of wavelet packets is to give richest analysis when compared with the wavelet transforms and thus adding more advantages to the performance of their proposed system.

In the early research of medical tumor detection, the algorithms have directly used the classic methods of image processing based on gray intensities of images. In recent years, the classification of human brain in MRI images is possible via supervised techniques such as k-nearest neighbor, Artificial



neural networks and support vector machines (SVM) and unsupervised classification techniques such as self-organization map and fuzzy C-means algorithm have also been used to classify the normal or pathological T2 weighted MRI images.

Glioma Tumor

Diffuse Low-Grade Gliomas (DLGG) is diffusely infiltrative essential cerebrum tumors

Meningioma Tumor

A meningioma is a primary central nervous system (CNS) tumor. This means it begins in the brain or spinal cord.

Pituitary Tumor

A pituitary tumor is an abnormal growth in the pituitary gland. But as pituitary adenomas grows, they can put pressure on nearby structures and can cause symptoms.

II. LITERATURE SURVEY

Various research work based on tumor types classification is taken place in last few years and improvement can be noticed. The proposed work consists of three types of tumor classification technique using the combination of CNN and machine learning. To reduce validation error, authors implemented genetic algorithm. Data normalization was used for rescaling the images and augmentation were taken place for perfect rotation before CNN architecture. Proposed method provided 94.2% accuracy.

Segmentation And Detection of Tumor in MRI Images Using CNN And SVM Classification

Among cerebrum tumors, gliomas are the most well-known what's more, forceful, prompting a short future in their most noteworthy review. In this way, treatment arranging is a key stage to move forward the oncological patients' personal satisfaction. SVM Classification is performed with the calculated parameters.

Diagnosing And Classification Tumors and MS Simultaneous of MRI Images Using CNN

Brain diseases such as brain tumors and MS diseases that are the most important means of detecting them using MRI imaging. By using this method, it can be accurately detecting the network for simultaneous diagnosis of tumor and MS with a accuracy of 96%.

Deep learning And Multi-Sensor Fusion For Glioma Classification Using Multi Stream 2D Convolution Networks

The main contributions of this work are: (a) propose a novel multi-stream deep CNN architecture for glioma grading; (b) apply sensor fusion from T1-MRI, T2-MRI and/or FLAIR for enhancing performance through feature aggregation; (c) mitigate overfitting by using 2D brain image slices in combination with 2D image augmentation.

Table 1: Literature Survey on Various Methods Used for Classification of Brain Tumor

S.No	METHODS	MODELS	IMAGES TAKEN	ACCURACY
1	10-fold cross validation, MRI using Deep Neural Network.	T1-Weighted using a contrast-enhanced MRI images database.	MRI images database 285 images (average)	96.56%
2	Deep Neural Network and incorporates a CNN based model	Tumor detected or No-tumor detected.	MRI images	96.08%
3	K-fold cross validation	Intensity histogram, gray-level co-occurrence matrix, and bag of words.	T1-Weighted contrast images glioma (1426 images), Meningioma (708), Pituitary (930)	91.28%
4	Convolution Neural Networks (CNN)	VGG-16 A pre-trained model.	small size datasets.	93%
5	CNN	Multi-sensor fusion scheme for gliomas	Images on glioma on high-grade & low-grade.	90.87%
6	CNN's which are machine learning pipelines modelled on the biological process of neurons and synapse.	Segmentation on brain tumors such as Glioblastoma & Astrocytomas.		82 to 90%

III. PROPOSED SYSTEM

Proposed Block Diagram

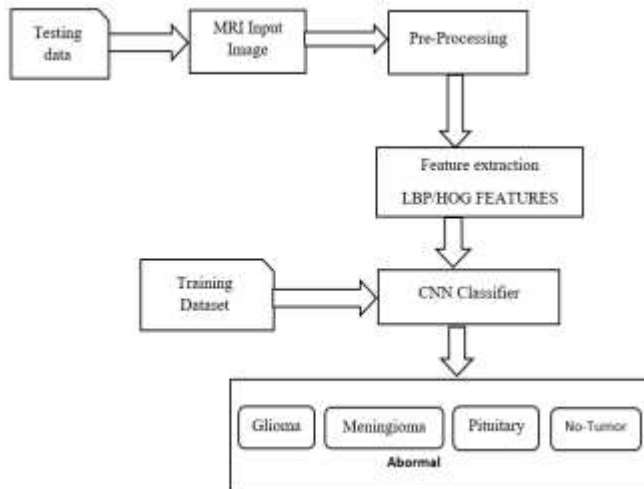


Fig 2. Framework of Proposed Methodology

Algorithm of Proposed Method

This proposed paper Deep CNN for three types of tumor classification. The proposed technique was executed in MATLAB R2019a. Overall method can be split up into four steps: pre-processing steps, feature extraction, classification step with CNN.

Step 1: Taking MRI brain tumor image from dataset

- Step 2: (a) Resize the input image
 (b) Use of Median filter to remove noise
 (c) Enhance the image contrast

- Step 3: (a) Feature extraction using HOG
 (b) Feature extraction using LBP

Step 4: Collecting features data for training

Step 5: Train the CNN with those data and see accuracy result.

Image Pre-Processing Steps

Input MRI images are needed processing for better classification accuracy. Sub-steps are described below:

RGB to Grayscale: The aim of the pre-processing is improvement of Block-Diagram as shown in Fig.3. Those image data are suppressing with undesired distribution and it was enhancing some image for the future.



Fig 3. Image pre-processing

Filtering:

Median filter is the type of filter provides a median value of the pixels of an image and it is used because the mean values obtained using averaging filters it makes image blur [7].

Resizing:

Resizing was done to make the equal size of all data. Resizing means to change the pixel information and it is resized 200*128 pixels.

Feature Extraction

LBP Features

LBP is a texture descriptor used for the property of high discrimination power.

Convert the image into grayscale space.

- 1- For each pixel(gp) in the image, select the P neighbourhoods that surround the central pixel. the coordinates of gp are given by
- 2- Take the centre pixel (gc) and set it as a threshold for its P neighbours.
- 3- Set to 1 if the value of the adjacent pixel is greater than or equal to the value of the centre pixel, 0 otherwise.
- 4- Now compute the LBP value: Sequentially counter clockwise, write a binary number consisting of digits adjacent to the centre pixel.

$$LBP(gp_x, gp_y) = \sum_{p=0}^{P-1} S(gp - gc) \times 2^p$$

HOG FEATURES

HOG, or Histogram of Oriented Gradients, is a feature descriptor that is often used to extract features from image data. Finally, the HOG would generate a Histogram for each of these regions separately.

Calculate the Gradient Images

To calculate a HOG descriptor, we need to first calculate the horizontal and vertical gradients; after all, we want to calculate the histogram of gradients.



With the following kernels. Next, we can find the magnitude and direction of gradient using the following formula

$$g = \sqrt{g_x^2 + g_y^2}$$

$$\theta = \arctan \frac{g_y}{g_x}$$

4.4 Convolution Neural Network

The convolution layers

Next, we turn to the convolution layer, which is the most involved, what is convolution? Let us start by convolving a matrix with one single convolution kernel. Suppose the input image is 3×4 and the convolution kernel size is 2×2 , as illustrated a 2×2 kernel.

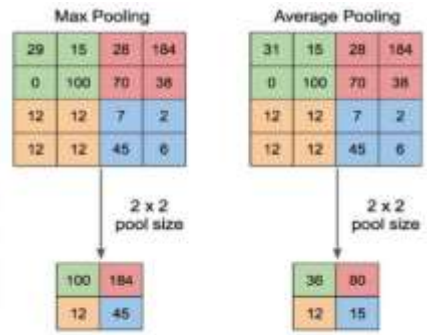


Fig 4. Max Pooling & Average Pooling

The pooling layers

Here the average pooling layer is used so that, it reduces the complexity of the data and improves the efficiency of the CNN.

Max Pooling 2d Layer: A 2-D max pooling layer performs down sampling by dividing the input into rectangular pooling regions, then computing the maximum of each region.

SYNTAX layer = maxPooling2dLayer (PoolSize, Name, Value)

RELU Layer: The training period is fastened by using Rectified Linear Unit.

Additional Layer: It is used to avoid the be-fitting of the other layers.

Soft-max Layer: This layer gives the output whether what type of tumor is present.

Fully-Connected Layer: The FC layer is where classification happens in the CNN based on the features extracted in the previous layers.

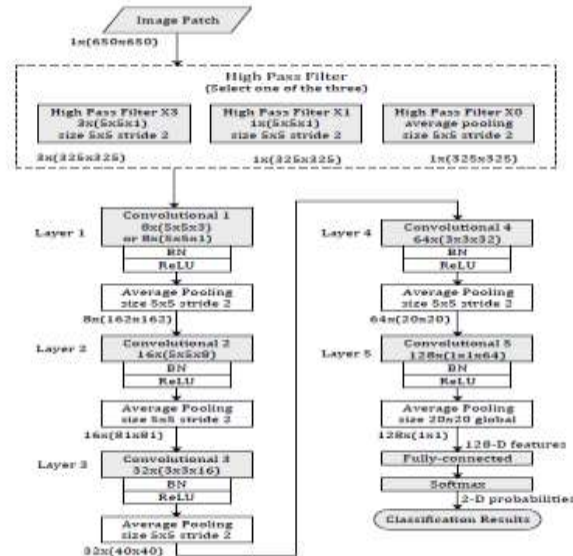


Fig 5. Proposed Convolutional Neural Network architecture

Classify: Classifies each row of the data in sample into one of the groups to which the data in training belongs. In fact, a key concept in CNN is distributed representation.

IV. RESULTS

Final Results

Training Set:

The training set plays an important part to train the model. From the dataset, the necessary information will be gathered by the program. Generally, 80% of the total dataset is used for the training purpose.

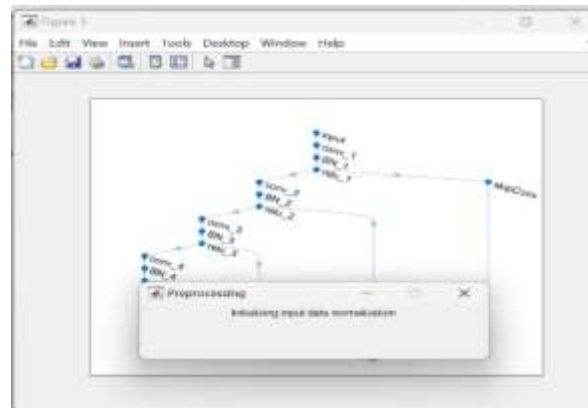


Fig 6. Input Data Normalization

In the above Fig 6. the Normalization of input data occurs so that, it can help the training data of the neural network with the different features which are on similar scale, that helps to stabilize the gradient descent step, allowing us to use larger learning rates or help models converge faster for a given learning rate.

Layer graph connects all the layers sequentially. Then, 1-by-1 convolutional layer is created and add to the layer graph. Specify the number of Convolutional filters and the stride so the activation size matches the activation size of relu_3 layer. This arrangement enables the additional layer to add the outputs of the skip Conv and relu_3 layers.

In simple terms, the additional layer is used to avoid the be-fitting between the layers. In this layer, the average pooling is used to determine the smooth features in the image. The SoftMax layer gives the class output if the tumor is present or not.



Fig 7. Training Progress

Here the epochs can be taken from 1 to 6. For 1 epoch, 20 iterations/ calculations are done. The epoch in the neural network means training the data for one cycle. Epoch can be understood as the number of times the algorithm scans the entire data. In the above Fig 7, there are two-different graphs i.e., accuracy and loss on y-axis and iteration on x-axis.

Validation /Testing Process

Pituitary Tumor

Fine-tuning helps to train the model. If the accuracy is not increasing for the validation set then the program is overfitting the model.

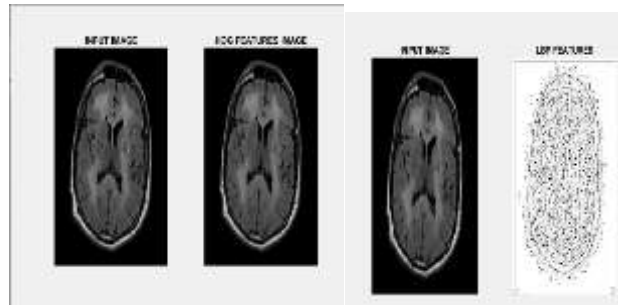


Fig 8. Feature Extraction from Pituitary Tumor using LBP & HOG

In the above Fig 8, LBP & HOG are the feature extraction methods that are used to determine the features in the image accordingly. The trained CNN model detects what type of tumor is present and gives result in Class output.



Fig 9.HOG features of Pituitary Tumor in blocks representation

After testing the image, the Accuracy of both CNN-LBP & CNN-HOG are calculated with the following epoch which was considered during training process. Also, the Mini-batch loss and accuracy of training dataset are also shown. Observe the following Fig 10.



Fig 10. Accuracies of CNN-LBP & CNN-HOG of Pituitary Tumor and Mini-Batch accuracy for training dataset

Glioma Tumor

In the below Fig11. LBP & HOG are the feature extraction methods that are used to determine the features in the image accordingly. To determine whether what type of tumor is present, first the image has to be given in 'Enter the Input' after completion of training process. When the input is read then the LBP & HOG featured images are occurred respectively.

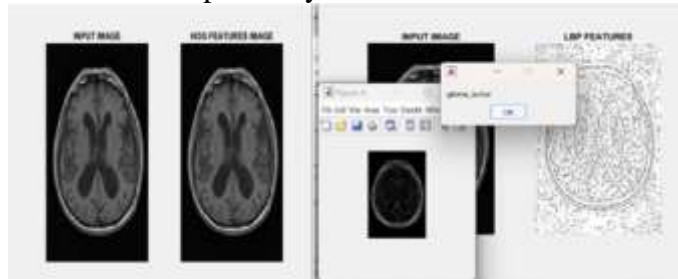


Fig 11. HOG & LBP Feature extraction from Detected Glioma Tumor

HOG is another feature extraction method that employs the image in blocks representation by calculating its orientations (directions) and gradients (magnitude of the image).

Meningioma Tumor

In the below figure 12., LBP & HOG are the feature extraction methods that are used to determine the features in the image accordingly. To determine whether what type of tumor is present, first the image has to be given in 'Enter the Input' after completion of training process.



Fig 12. HOG & LBP Feature extraction from Detected Meningioma Tumor

No-Tumor

The process involves thresholding the center pixel of the window with its surrounding pixels using the window mean, window median or the thresholds.

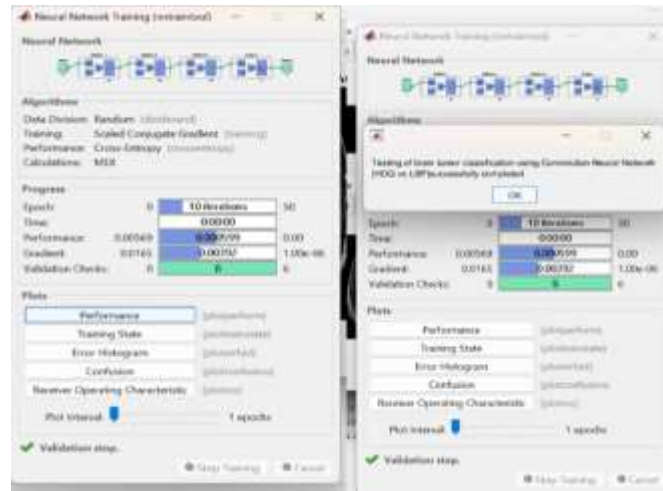


Fig 13. Progress for Neural network tool

Upon testing the images, the final message is shown like Testing of brain tumor using Convolution Neural Network (HOG vs LBP) successfully completed with the neural network training tool that implies showing the progress of Epoch, Elapsed time, Performance, Gradient and the Validation checks.

Table 2. Represents the Mini-batch Accuracy, Mini-batch loss, CNN-LBP & CNN-HOG Accuracy.

S.NO	INPUT IMAGE	TYPE OF TUMOR DETECTED	MINI-BATCH ACCURACY	MINI-BATCH LOSS	CNN-LBP ACCURACY	CNN-HOG ACCURACY
1.	Img1.jpg	Pituitary Tumor	60.16%	1.0972	98%	97.7%
2.	Img14.jpg	Glioma Tumor	54.69%	1.1247	97.3%	97.7%
3.	Img9.jpg	Meningioma Tumor	50.00%	1.2355	97.3%	93.3%
4.	Img10.jpg	Meningioma tumor	50.78%	1.1269	96%	97.7%
5.	Img17.jpg	Glioma Tumor	60.94%	0.9567	98.6%	97.7%
6.	p.jpg	Pituitary Tumor	62.50%	1.0828	96.6%	97.7%
7.	Img22.jpg	No Tumor	60.94%	1.2284	97.3%	97.6%

V. CONCLUSION & FUTURE SCOPE

Finally, Glioma, meningioma, and pituitary tumor types classification technique using Convolution neural network is proposed in this paper. This proposed method works in this manner and works with brain tumor data. Images consisted of low contrast quality. Proposed technique provided better accuracy for LBP features than HOG features at most of the cases. The accuracy is more for the LBP for all most all cases than HOG. Obtained accuracy is much better than various existing classification techniques and this is less complex.

In future, authors are interested to improve this accuracy by different demonstrations. In all such cases, the proposed algorithm must be robust enough for accurate recognition of tumor regions from MR Images. The proposed approach can be further improvised through in cooperating weakly trained algorithms that can identify the abnormalities with a minimum training data and also self-learning algorithms would aid in enhancing the accuracy of the algorithm and reduce the computational time. Also,



the CNN algorithm can be improvised on detecting various tumors on other organs which can help in medical field.

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