

Brain Tumor Detection using Deep Learning

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Abstract - Medical image processing is that the one among the foremost demanding and promising field nowadays. Tumor is a rapid uncontrolled growth of cell. The tumor are often classified as benign, malignant and premalignant. When a tumor is noticed as malignant then the tumor results in cancer. Earlier stage of tumor is used to be detected manually through observation of image by doctors and it takes more time and sometimes gets inaccurate results. Today different computer added tool is employed in medical field. These tools provide a quick and accurate result. Magnetic Resonance Images (MRI) is the most widely used imaging technique for analyzing internal structure of human body. The MRI is used even in diagnosis of most severe disease of medical science like brain tumors. The brain tumor detection process consist of image processing techniques involves four stages. Image pre-processing, image segmentation, feature extraction, and finally classification. There are several existing of techniques are available for brain tumor segmentation and classification to detect the brain tumor. There are many techniques available presents a study of existing techniques for brain tumor detection and their advantages and limitations. To overcome these limitations, propose a Convolution Neural Network (CNN) based classifier. CNN based classifier does the comparison between trained and test data, from this to get the simplest result.

Keywords: Brain Tumor Detection, CNN, Image Pre-processing

1. INTRODUCTION

Brain is that the management center within the physical body. It is responsible to execute all activities throughout a large number of connections and a huge number of neurons. Brain tumor is one of the most serious diseases, occurred due to an abnormal growth of cells in the brain, affecting the functions of the nervous system. There are different types of brain tumors which can be either malignant or benign.

The early stage of tumor detection depends on the physician's knowledge and experience, making the patients have a chance to recover his life and survival. An automated classification system of brain tumors is an effective tool for supporting the physicians to follow a successful treatment option. Such system uses the images captured by magnetic resonance (MR) imaging devices which are widely used by the radiologists of brain diagnosis.

Malignant brain tumors are usually in the form of blood clots accompanied by fat surrounding it. To detect the location and size of brain tumors required MRI images of brain tumors. MRI images can help differentiate brain tissue, brain tumors, edema, and spinal fluid supported differences in color contrast in each tissue. The problem in radiological remains analyzing the results of MRI brain tumour manually in order that it takes an extended time to seek out out the diagnostic from the doctor.

Image processing is a process of analyzing, manipulating a picture so as to perform some operation to extract the knowledge from it. According to world health organization's statistics, cancer is considered as the second leading cause of human fatalities across the world, being responsible for an estimated 9:6 million deaths in this year. Among different form of cancers, brain tumor is widely seen together of the deadliest cancers because of its aggressive nature, heterogeneous characteristics (types), and low relative survival rate (e.g., in US relative survival rate following a diagnosis of a primary malignant brain tumour is around 35%).

Medical imaging seeks for disclosure of internal structures hidden by skin and bones and also to diagnose and treat disease. And also, it establishes a database of normal anatomy and physiology to form it possible to sense abnormalities.

In today's world, one of the reasons in the rise of mortality among the people is brain tumor. Abnormal or uncontrolled growth of cell developed inside the human body is called brain tumor.

This group of tumor grows within the skull, due to which normal brain activity is disturbed. Brain tumor is a serious life frightening disease. So, which not detected in earlier stage, can take away person's life. Brain tumors are often mainly three varieties called benign, malignant, pre-malignant. The malignant tumor leads to cancer.

1.1 CNN

Convolutional neural network(CNN, or ConvNet) is type of profound learning and most usually applied to dissecting visual symbolism.CNNs utilize a variety of multilayer perceptron's intended to require negligible pre-processing.They are moreover insinuated as move invariant or space invariant artificial neural network(SIANN), supported their normal burdens structure and translation invariance characteristics.

Convolutional networks were propelled by natural procedures in that the availability design between neurons takes after the association of the creature visual territory . Individual cortical neurons answer stimuli only during a restricted region of the field of vision referred to as the receptive field. The receptive fields of various neurons partially overlap such they cover the whole field of vision .CNNs utilize moderately little pre-preparing contrasted with other image classification algorithm. This implies the system learns the channels that in customary calculations were hand-built. This autonomy from earlier information and human exertion in include configuration might be a significant bit of leeway.They have applications in image and video recognition, recommender systems, image classification, medical image analysis, and tongue processing.

A CNN consists of an input and an output layer, also as multiple hidden layers. The hidden layers of a CNN typically contains convolutional layers, pooling layers, fully connected layers and normalization layers.

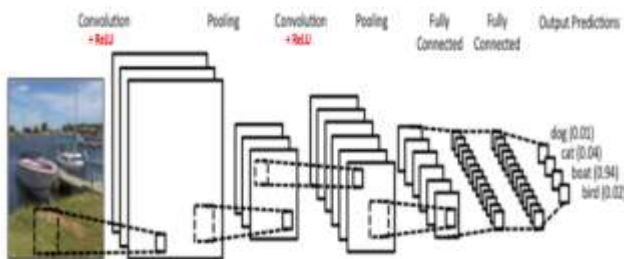


Fig1. Simple ConvNet.

There are four primary activities in the ConvNet appeared in fig. above:

1. Convolution
2. Non-Linearity (ReLU)
3. Pooling or Sub Sampling
4. Classification (Fully Connected Layer)

The Convolution Step:

The main objective of Convolution is to gather features from the input image. Convolution conserves the spatial relationship within pixels by learning image features using small squares of input data. Here every image can be considered as a matrix of pixel values. Let’s consider a 5 x 5 image whose pixel values are only 0 and 1, the 5x5 matrix is a special case where pixel values are 0 and 1.

1	1	1	0	0	1	0	1
0	1	1	1	0	0	1	0
0	0	1	1	1	1	0	1
0	0	1	1	0			
0	1	1	0	0			

Also, consider another 3 x 3 matrix as kernel. Then, the Convolution of the 5 x 5 image and the 3 x 3 matrix can be computed as given below:

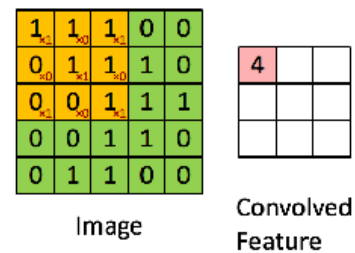


Fig2. The Convolution operation

The output matrix is called Convolved Feature. We slide the orange matrix over our original image by 1 pixel (called ‘stride’) and for every position, we compute element wise multiplication and add the multiplication outputs to get the final integer which forms a single element of the output matrix.

As an example, consider the following input image: It is evident from the animation above that different values of the filter matrix will produce different Feature Maps for the same input image. As an example, consider the following input image:



Fig3. Sample Image

In the table below, we will see the consequences of convolution of the above image with different filters. As shown, we will perform operations like Edge Detection, Sharpen and Blur just by changing the numeric values of our filter matrix before the convolution operation– this suggests that different filters can detect different features from a picture , for instance edges, curves etc.








Operation	Filter	Convolved Image
Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
Edge detection	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
Box blur (normalized)	$\frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	
Gaussian blur (approximation)	$\frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$	

Fig4. Various Operation on Sample Image

Introducing Non-Linearity (ReLU):

An additional operation called ReLU has been used after every Convolution operation. ReLU stands for Rectified linear measure and may be a non-linear operation. Its output is given by:



ReLU is an applied per pixel and replaces all pixels valued negative in the feature map by zero. The objective of ReLU is to present the non-linearity in our ConvNet, as majority of real-world data we need our ConvNet to learn would be non-linear (Convolution is a linear operation – element wise matrix operation and addition, so we account for non-linearity by presenting a non-linear function like ReLU).

The Pooling Step:

Spatial Pooling reduces the dimensionality of each feature map but keeps the important information. Spatial Pooling are of numerous types like Average, Sum, Max etc.

In Max Pooling, we need to define a spatial neighborhood and take the largest element from the corrected feature map within that window. Instead of taking the largest element we could also take the average or sum of all elements in that window. In practice, Max Pooling has been shown to figure better.

Shows an example of Max Pooling operation on a Rectified Feature map (obtained after convolution + ReLU operation) by employing a 2x2 window.

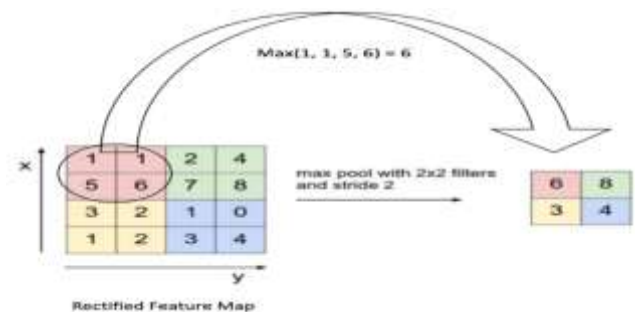


Fig5. Max Pooling

We slide our 2 x 2 window by 2 cells (also called 'stride') and take the maximum value from each region. This process reduces the dimensionality of our feature map.

1.2 SVM

Support Vector Machines (SVMs) square measure supervised learning models with associated learning algorithms that analyze knowledge used for classification and statistical procedure. Given a gaggle of coaching examples, each marked as belonging to a minimum of 1 or the opposite of two categories, an SVM training algorithm builds a model that assigns new examples to a minimum of 1 category or the opposite, making it a non-probabilistic binary linear classifier (although methods like Platt scaling exist to use SVM during a probabilistic classification setting). An SVM model could even be a representation of the examples as points in space, mapped so as that the samples of the separate categories are divided by a transparent gap that's as wide as possible. New examples are then mapped into that very same space and predicted to belong to a category supported the side of the gap on which they fall.

A Support Vector Machine develops a hyperplane or set of hyperplanes during a high-or unending dimensional space, which can be utilized for characterization, relapse, or different errands like exceptions detection.[3] Intuitively, a fair partition is accomplished by the hyperplane that has the first significant separation to the nearest preparing information purpose of any class (supposed useful edge), since for the most part the bigger the edge, the lower the speculation blunder of the classifier. A Support Vector Machine (SVM) could even be a discriminative classifier formally defined by a separating hyperplane. As it were, given named preparing information (managed learning),

the calculation yields an ideal hyperplane which sorts new models. In two dimensional space this hyperplane could even be a line dividing a plane in two parts where in each class lay in either side.

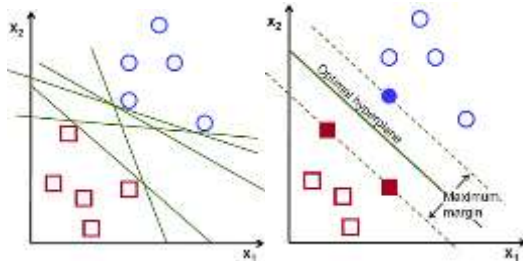


Fig6. Hyperplanes

2. Literature Survey

[1] Abdu Gumaiei, Mohammad Mehedi Hassan

Cerebrum malignant growth characterization could likewise be a significant advance that relies upon the doctor's information and information. an automatic tumor arrangement is extremely essential to support radiologists and physicians to spot brain tumors. However, the accuracy of current systems got to be improved for suitable treatments. during this paper, we propose a crossover highlight extraction strategy with regularized outrageous learning machine for building up an exact cerebrum tumor arrangement approach. The methodology begins by separating the highlights from brain pictures utilizing the mixture include extraction technique; at that point, registering the covariance network of those highlights to extend them into a replacement significant set of features using principle component analysis (PCA). Finally, a regularized extreme learning machine (RELM) is employed for classifying the sort of brain tumour . to gauge and compare the proposed approach, a gaggle of experiments is conducted on a replacement public dataset of brain images. Experimental results proved that the approach is simpler compared to the existing state-of-the-art approaches, and thus the performance in terms of classification accuracy improved from 91.51% to 94.233% for the experiment of random holdout technique.

[2] Annisa Wulandari, Riyanto Sigit

Brain tumor is one among disease type that attacks the brain within the sort of clots. there's how to ascertain brain tumour intimately requires by an MRI image. there's difficulty in distinguishing brain tumour tissue from normal tissue due to the similar color. brain tumour must be analyzed accurately. the answer for analyze brain tumour is doing segmentation. brain tumour segmentation is completed to separate brain tumour tissue from other tissues like fat, enema, normal brain tissue and spinal fluid to beat this difficulty, The MRI image must be maintained at the sting of the image first with the median filtering. Then the tumor segmentation process requires

thresholding method which is then iterated to require the most important area. The brain segmentation is completed by giving a mark on the world of the brain and areas outside the brain using watershed method then clearing skull with cropping method. during this study, 14 brain tumour MRI images are used. The segmentation results are compared brain tumors area and brain tissues area. this technique obtained the calculation of tumor area has a mean error of 10%.

[3] Mircea Gurbin

The brain is one among the foremost complex organs within the physical body that works with billions of cells. A cerebral tumor occurs when there's an uncontrolled division of cells that form an abnormal group of cells around or within the brain. This cell group can affect the traditional functioning of brain activity and may destroy healthy cells. Brain tumors are named considerate or second rate (grade 1 and 2) and dangerous tumors or high (grade 3 and 4). The proposed strategy expects to separate between ordinary cerebrum and tumor brain (considerate or insult). The study of some sorts of brain tumors like metastatic bronchogenic carcinoma tumors, glioblastoma and sarcoma are performed using brain resonance imaging (MRI). The detection and classification of MRI brain tumors are implemented using different wavelet transforms and support vector machines. Accurate and automatic classification of MRI brain images is extremely important for medical analysis and interpretation.

[4] Parnian Afshar, Konstantinos N. Plataniotis

According to official statistics, cancer is taken into account because the second leading explanation for human fatalities. Among varying kinds of malignant growth, brain tumor is seen together of the deadliest structures on account of its forceful nature, heterogeneous qualities, and low relative endurance rate. Determining the sort of brain tumour has significant impact on the treatment choice and patient's survival. Human-focused finding is normally blunder inclined and questionable prompting an ongoing flood important to automatize this procedure utilizing convolutional neural systems (CNNs). CNNs, be that as it may, neglect to totally use spatial relations, which is particularly destructive for tumor grouping, in light of the fact that the connection between the tumor and its encompassing tissue might be a basic marker of the tumor's sort. In our recent work, we've incorporated newly developed CapsNets to beat this shortcoming. CapsNets are, however, sensitive to the miscellaneous image background. The paper addresses this gap. the most contribution is to equip CapsNet with access to the tumor surrounding tissues, without distracting it from the most target. An adjusted CapsNet architecture is, in this manner, proposed for brain tumor characterization, which takes the tumor coarse limits as additional contributions inside its pipeline to expand the CapsNet's core interest. The proposed approach discernibly outflanks its partners.

[5] T. M. Shahriar Sazzad, Misbah Ul Hoque

A tumor cell may be a sort of cell that develops out of control of the standard forces and standardizes growth. brain tumour is one among the main reasons for fatality per annum . Around 50% of brain tumour diagnosed patient die with primary brain tumors annually within the us . Electronic modalities are wont to diagnose brain tumors. Among all electronic modalities, resonance Imaging (MRI) is one among the foremost used and popular for brain tumour diagnosis. during this research study, an automatic approach has been proposed where MRI gray-scale images were incorporated for brain tumour detection. This study proposed an automatic approach that has enhancement at the initial stage to attenuate gray-scale color variations. Filter operation was wont to remove unwanted noises the maximum amount as possible to help better segmentation. As this study test grayscale images therefore; threshold based OTSU segmentation was used rather than color segmentation. Finally, pathology experts provided feature information was wont to identify the region of interests (brain tumor region). The experimental results showed that the proposed approach was ready to perform better results compared to existing available approaches in terms of accuracy while maintaining the pathology experts' acceptable accuracy rate.

[6] Chuanlu Lin, Yi Wang, Tianfu Wang, Dong Ni

We present a typical system for the synchronous division and recuperation of obsessive magnetic resonance (MR) brain pictures, where low-rank and sparse decomposition (LSD) plans have been generally utilized. Conventional LSD methods often produce recovered images with distorted pathological regions, due to the lack of constraint between low-rank and sparse components. To address this issue, we propose a transformed low-rank and structured sparse decomposition (TLS2D) method, which is robust for extracting pathological regions. Also, the all around recuperated pictures can be acquired utilizing both organized inadequate and figured picture saliency as the versatile sparsity requirement. Experimental results on MR brain tumor images demonstrate that our TLS2D can effectively provide satisfactory performance on both image recovery and tumor segmentation.

[7] Sérgio Pereira, Adriano Pinto, Victor Alves

Among brain tumors, gliomas are the foremost common and aggressive, leading to a very short anticipation in their highest grade. Thus, treatment planning could also be a key stage to reinforce the quality of lifetime of oncological patients. Magnetic resonance imaging (MRI) could likewise be a broadly utilized imaging method to survey these tumors, however the gigantic measure of information delivered by MRI forestalls manual division during an inexpensive time, limiting the use of precise

quantitative measurements within the clinical practice. Along these lines, programmed and dependable division strategies are required; be that as it may, the immense spatial and basic fluctuation among brain tumors make automatic segmentation a difficult issue. during this paper, we propose an automatic segmentation method supported Convolutional Neural Networks (CNN), exploring small 3x3 kernels. the utilization of little bits permits structuring a more profound design, other than having a constructive outcome against overfitting, given the less number of loads inside the system. We additionally researched the utilization of force standardization as a pre-handling step, which however not normal in CNN-based division strategies, demonstrated related to information expansion to be exceptionally viable for mind tumor division in MRI pictures. Our proposition was approved inside the mind tumor Segmentation Challenge 2013 database (BRATS 2013), getting all the while the principal position for the entire , center, and improving districts in Dice Similarity Coefficient metric (0.88, 0.83, 0.77) for the Challenge informational collection. Additionally, it acquired the general first situation by the online assessment stage. We additionally took an interest inside the on location BRATS 2015 Challenge utilizing a similar model, acquiring the subsequent spot, with Dice Similarity Coefficient metric of 0.78, 0.65, and 0.75 for the entire, center, and upgrading areas, separately.

3. Proposed System

As per literature survey, it had been found that automated brain tumour detection is extremely necessary as high accuracy is required when human life is involved. Automated detection of tumor in MR images involves feature extraction and classification using machine learning algorithm. Our approach consists of three steps: (A) Brain image pre-processing, (B) Brain feature extraction, and (C) brain tumour classification. The input of the approach is that the brain images and therefore the output are the respective sort of the brain tumour. The small print of the steps of our proposed approach are described within the subsections below. during this paper, a system to automatically detect tumor in MR images is proposed as shown in figure 3.

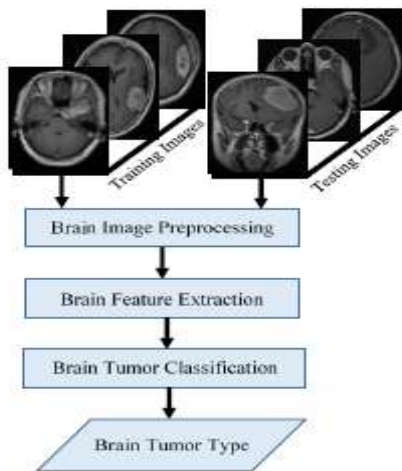


Fig7. Proposed System

A. Image Pre-processing

Pre-preparing might be a typical name for activities with pictures at absolute bottom degree of deliberation both info and yield are intensity images.

The purpose of pre-handling with is an improvement of the picture data that smothers unfortunate curves or redesigns some picture features huge for extra handling. The reason for picture preparing is separated into 5 gatherings.

They are:

1. Perception - Observe the articles that are not obvious.
2. Picture honing and rebuilding - To make a superior picture.
3. Picture recovery - Seek for the picture of intrigue.
4. Estimation of example – Measures different articles in a picture.
5. Picture Recognition – Distinguish the items in a picture.

a. Gray Scale

Grayscale picture otherwise called highly contrasting picture is the one wherein every pixel of the picture conveys power data. Dim scale picture has just two hues: Black and white. The changed over grayscale picture may lose contrasts, sharpness, shadow, and structure of the shading picture. The luminance of a pixel estimation of a grayscale picture ranges from 0 to 255.

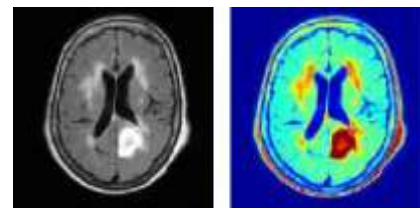


Fig8.Gray Scale Image

b. Smoothing

The low-pass filters for the most part utilize moving window administrator which influences each pixel of the picture in turn, changing its incentive by some capacity of a local region (window) of pixels. The administrator moves over the picture to influence all the pixels in the picture. The operator moves over the image to affect all the pixels in the image.



Fig 9. Smoothing

c. Edge Detection

Watchful edge recognition is a used to remove valuable basic data from various articles and lessen the measure of information to be handled. The general criteria for edge recognition incorporate: -

1. Detection of edge with low blunder rate, which implies that the discovery ought to precisely get however many edges appeared in the picture as could reasonably be expected.
2. The edge point identified from the administrator ought to precisely confine on the focal point of the edge.
3. A given edge in the picture should just be checked once, and where conceivable, picture clamor ought not make bogus edges.

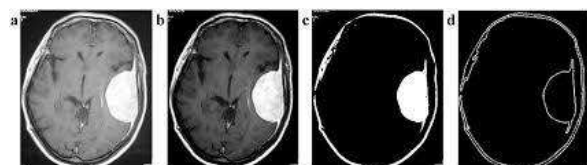


Fig10.Edge Detection

4. CONCLUSION

In summary, we propose a CNN-based method for segmentation of brain tumors in MRI images. There are several existing of techniques are available for brain tumor segmentation and classification to detect the brain

tumor. There are many techniques available presents a study of existing techniques for brain tumor detection and their advantages and limitations. To overcome these limitations, propose a Convolution Neural Network (CNN) based classifier. CNN based classifier used to compare the trained and test data, from this get the best result.

REFERENCES

- [1] D. Kornack and P. Rakic, "Cell Proliferation without Neurogenesis in Adult Primate Neocortex," *Science*, vol. 294, Dec. 2001, pp. 2127-2130, doi:10.1126/science.1065467.
- [2] M. Young, *The Technical Writer's Handbook*. Mill Valley, CA: University Science, 1989.
- [3] R. Nicole, "Title of paper with only first word capitalized," *J. Name Stand. Abbrev.*, in press.
- [4] K. Elissa, "Title of paper if known," unpublished.
- [5] Zeynettin Akkus, Alfiia Galimzianova, Assaf Hoogi , Daniel L. Rubin and Bradley J. Erickson, "Deep Learning for Brain MRI Segmentation: State of the Art and Future Directions" *J Digit Imaging* DOI 10.1007/s10278-017- 9983-4, 2017.
- [6] Anupurba Nandi, "Detection of human brain tumour using MRI image segmentation and morphological operators" *IEEE International Conference on Computer Graphics, Vision and Information Security (CGVIS)*, 2015.
- [7] Swapnil R. Telrandhe, Amit Pimpalkar and Ankita Kendhe, "Detection of Brain Tumor from MRI images by using Segmentation &SVM" *World Conference on Futuristic Trends in Research and Innovation for Social Welfare (WCFTR'16)*, 2016.