



Brain Tumor Detection Using Deep Learning Algorithm

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ABSTRACT: Medical image processing is most important and demanding field. Tumor is a rapid uncontrolled growth of cell. Tumor is classified into three-stage benign, malignant and pre-malignant. When the tumor is malignant it leads to cancer. Different computer tool are used in medical field. These tools provide quick response and accurate result. MRI techniques are used for analyzing internal structure of human body. MRI is used to diagnose different types of diseases in medical field like brain tumors. The techniques involves four stages are Image pre-processing, Image segmentation, feature extraction, and finally classification. There are various existing of techniques are available for brain tumor segmentation and classification for this technique they have advantages and limitations. To overcome these limitations, propose a CNN based classifier. It is used to compare trained and test data, from this get the best result.

KEYWORDS: Brain Tumor Detection, CNN, Image Pre-processing, MRI

I. INTRODUCTION

The image processing is a process of analyzing, manipulating an image to perform some operation to extract the information from it. Medical imaging seeks to diagnose and treat disease. And also it establishes a database of normal anatomy and physiology to make it possible to identify abnormalities. Abnormal or uncontrolled growth of cells developed inside the human body is called a brain tumor. The tumor grows within the skull, due to this normal brain activity is disturbed. Brain tumor is a serious life threatening disease. So which not detected in an earlier stage, can take a person life away. Tumor is classified into three-stage benign, malignant, pre-malignant. The malignant tumor leads to cancer. Treatment of brain tumor depend on various factor such as proper diagnoses, location, size, type of tumor, and stage of development. Earlier stage tumor is used to detect manually through observation of image by the doctor and it takes more time. Different computer tools are used in the medical field. These tools provide quick response and accurate result. MRI is the most commonly used imaging technique for analysing the internal structure of the human body. Proper detection of tumors is the proper solution of treatment. Detection involves the diagnosis of the presence of the tumor. The technique involves four stages of image processing they are image pre-processing, image segmentation, feature extraction, and finally classification. Pre-processing is to improve the quality of Magnetic Resonance (MR) images, removing unwanted noise and undesired parts in the background and preserving its edges. In segmentation the pre-processed brain MR image is converted into binary images. Feature extraction is the process of collecting higher-level information of image such as color, texture, contrast and shape. And the classification process, the classifier is used to classify the normal trained image samples and input image sample.

II. LITERATURE SURVEY

[1] Capsule Networks For Brain Tumor Classification Based On Mri Images And Coarse Tumor Boundaries

The author has explained that human centered diagnosis is typically error-prone and unreliable resulting in a recent surge of interest to automatize this process using convolutional neural networks (CNNs). CNNs, however, fail to fully utilize spatial relations, which are particularly harmful for tumor classification, as the relation between the tumor and its surrounding tissue is a critical indicator of the tumor's type. We have incorporated newly developed CapsNets to

overcome this shortcoming. CapsNets are highly sensitive to the miscellaneous image background. The main contribution is to equip CapsNet with access to the tumor surrounding tissues, without distracting it from the main target. A modified CapsNet architecture is, therefore, proposed for brain tumor classification, which takes the tumor coarse boundaries as extra inputs within its pipeline to increase the CapsNet's focus. The proposed approach noticeably outperforms its counterparts.

[2] A Hybrid Feature Extraction Method with Regularized Extreme Learning Machine for Brain Tumor Classification

The author has explained that, a hybrid feature extraction method with regularized extreme learning machine for developing an accurate brain tumor classification approach. The approach starts by extracting the features from brain images using the hybrid feature extraction method; then, computing the covariance matrix of these features to project them into a new significant set of features using principle component analysis (PCA). Finally, a regularized extreme learning machine (RELM) is used for classifying the type of brain tumor. To evaluate and compare the proposed approach, a set of experiments is conducted on a new public dataset of brain images. Experimental results proved that the approach is more effective compared to the existing state-of-the-art approaches, and the performance in terms of classification accuracy improved from 91.51% to 94.233% for the experiment of random holdout technique.

[3] Tumor Detection and Classification of MRI Brain Image using Different Wavelet Transforms and Support Vector Machines

The author has explained that Brain tumors are classified as benign or low-grade (grade 1 and 2) and malignant tumors or high-grade (grade 3 and 4). The proposed methodology aims to differentiate between normal brain and tumor brain (benign or malign). The study of some types of brain tumors such as metastatic bronchogenic carcinoma tumors, glioblastoma and sarcoma are performed using brain magnetic resonance imaging (MRI). The detection and classification of MRI brain tumors are implemented using different wavelet transforms and support vector machines. Accurate and automated classification of MRI brain images is extremely important for medical analysis and interpretation.

[4] Segmentation And Recovery Of PathologicalMri Brain Images Using Transformed Low-Rank And Structured Sparse Decomposition

The author have explained that 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. Moreover, the well recovered images can be obtained using both structured sparse and computed image saliency as the adaptive sparsity constraint. Experimental results on MR brain tumor images demonstrate that our TLS2D can effectively provide satisfactory performance on both image recovery and tumor segmentation.

[5] Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images

The author has explained that Magnetic resonance imaging (MRI) is a widely used imaging technique to assess these tumors, but the large amount of data produced by MRI prevents manual segmentation in a reasonable time, limiting the use of precise quantitative measurements in the clinical practice. So, automatic and reliable segmentation methods are required; however, the large spatial and structural variability among brain tumors make automatic segmentation a challenging problem. In this paper, we propose an automatic segmentation method based on Convolutional Neural Networks (CNN), exploring small 3 3 kernels.

[6] Development of Automated Brain Tumor Identification Using MRI Images

The author has explained that Magnetic Resonance Imaging (MRI) is one of the most used and popular for brain tumor diagnosis. In this research study, an automated approach has been proposed where MRI gray-scale images were incorporated for brain tumor detection. This study proposed an automated approach that includes enhancement at the initial stage to minimize gray-scale color variations. Filter operation was used to remove unwanted noises as much as possible to assist better segmentation. As this study test grayscale images therefore; threshold based OTSU segmentation was used instead of color segmentation. Finally, pathology experts provided feature information was used to identify the region of interests (brain tumor region). The experimental results showed that the proposed approach

was able to perform better results compared to existing available approaches in terms of accuracy while maintaining the pathology experts' acceptable accuracy rate.

[7] Brain Tumor Segmentation to Calculate Percentage Tumor Using MRI

The author has explained that brain tumor segmentation is done to separate brain tumor tissue from other tissues such as fat, edema, normal brain tissue and cerebrospinal fluid to overcome this difficulty. The MRI image must be maintained at the edge of the image first with the median filtering. Then the tumor segmentation process requires thresholding method which is then iterated to take the largest area. The brain segmentation is done by giving a mark on the area of the brain and areas outside the brain using watershed method then clearing skull with cropping method.

III. PROPOSED SYSTEM

As per the literature survey, automated brain tumor detection is very important as high accuracy is needed when human life is involved. Automated detection of tumors in MRI images involves feature extraction and classification using a machine learning algorithm. The proposed system as shown in figure.

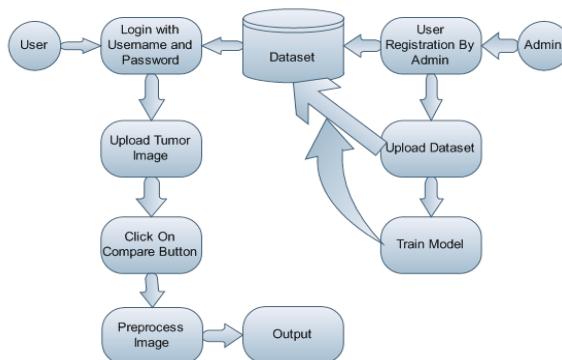


Fig.1:- System Architecture

IV. METHODOLOGY

Convolutional neural network (CNN or ConvNet) is a form of deep learning and most important to analysing visual imagery. CNNs uses a multilayer perceptrons designed to require minimal pre-processing. They are also known as shift invariant or space invariant artificial neural network (SIANN). Individual cortical neurons respond to stimuli only in a restricted region of the visual field called as the receptive field. Different neurons partially overlap to cover the entire visual field.

Application based image and video recognition, recommender system, medical image analysis, image classification, and natural language processing. A CNN consist of input and output layer as well as multiple hidden layers. The hidden layer consists of convolution layers, pooling layers, normalization layers, and fully connected layers.

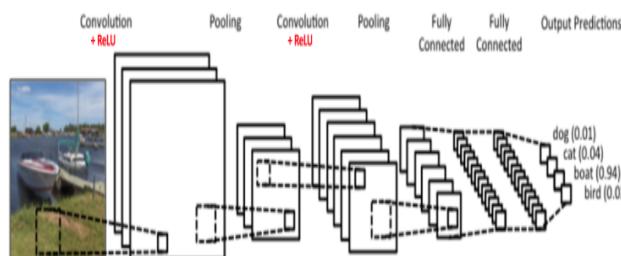


Fig 2:- Simple ConvNet

The figure above shows Convolution Neural Network architecture to the LeNet and classifies an input image into four categories dog, cat, goat or bird. Four main operations in the ConvNet shown in fig above.

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

The Convolution Step:

ConvNets derive their name from the “convolution” operator. ConvNet is to extract feature from the input image. Convolution the spatial relationship between pixels by learning image features using small squares of input data. Every image can be considered as a matrix of pixel value. Consider a 5×5 image whose pixel value range values are 0 and 1. (Note – grayscale image, pixel values range from 0 to 255, the green matrix below whose pixels values are only 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 3×3 matrix as shown. The convolution of the 5×5 image and 3×3 matrix can be shown in fig below:

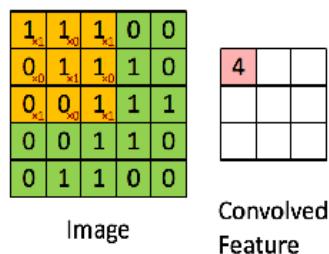


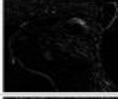
Fig 3:- Convolution operation

The output matrix is called Convolved Feature or Feature Map. Slide the orange matrix over our original image (green) by 1 pixel (called as stride) and for every position, compute element wise multiplication (between 2 matrices) and add the multiplication output to get the final integer which forms single element of the output matrix (pink).

Note In CNN terminology, the 3×3 matrix is called a ‘filter’ or ‘kernel’ or ‘feature detector’ and the matrix formed by sliding the filter over the image and computing the dot product is called the ‘Convolved Feature’ or The Feature Map. The animation above that different values of the filter matrix will produce different feature maps for the same input image. Consider the following example as input image: the animation above that different values of the filter matrix will produce different feature for the same input image.



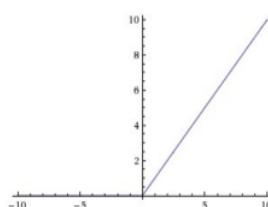
In the table below, we can see the effects of convolution of the above image with different filters. As shown, we can perform operations such as Edge Detection, Sharpen and Blur just by changing the numeric values of our filter matrix before convolution operation that means the different filters can detect different features from an image, E.g- edge, 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)	$\frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$	

Introducing Non Linearity (ReLU):

An additional operation called ReLU is used for convolution operation in figure above. ReLU stands for rectified Linear Unit and is a non-linear operation. Its output is given as

$$\text{Output} = \text{Max}(0, \text{Input})$$



ReLU is an element wise operation and replaces all negative pixel values in the feature map by zero. (Convolution is a linear operation- element wise matrix multiplication and addition, so we account for non-linearity by introducing a non-linear function like ReLU).

The Pooling Step:

Spatial Pooling (also called subsampling or downsampling) reduces the dimensionality of each feature map but retains the most important information. They have different types: Max, Average, Sum etc.

Max pooling, we define a spatial neighbourhood and take largest element from rectified feature map within that window. Instead of taking largest number we also take average value or sum of all elements in window. For example – max pooling operation on a rectified feature map (obtained after convolution + ReLU operation) by using 2 x 2 window.

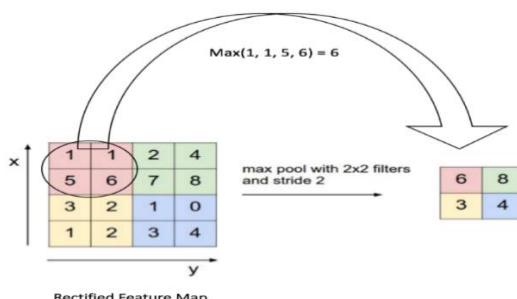


Fig.5:-Max Pooling

Slide our 2x 2 window by 2cells (also called ‘stride’) and take maximum value in each region. As shown in figure, this reduces the dimensionality of our feature map.

IV. CONCLUSION

The proposed system is CNN based method for the segmentation of brain tumor in MRI images. Several existing techniques are available for brain tumor segmentation and classification to detect the brain tumor for this technique they have 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 results.

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