ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com
International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 5, Special Issue 7, March 2018

BRAIN TUMOR SEGMENTATION USING CNN AND GLCM IN MRI IMAGES

Mrs.A.Poojaa[1], A.Rajeshwari[2], P.Suruthi[3], J.Jenova[4], M.Nithya[5].

Assistant Professor, Bharathiyar Institute of Engineering for Women, Deviyakurichi, Salem, India.[1]

UG Scholar, Bharathiyar Institute of Engineering for Women, Deviyakurichi, Salem, India.[2,3,4,5]

ABSTRACT

Meningioma, Glioma and pituitary are the most common and aggressive disease in brain tumor, leading to a very short life expectancy in their highest grade. The diagnostic values of MRI are greatly increased by the automated and accurate classification of the MRI brain images. Accurate detection of the type of brain abnormality is highly essential to minimize the fatal results. Thus propositioned method entails the treatment planning is a key stage to improve the quality of life of tumor patients. Convolutional Neural Networks (CNN), exploring small 3x3 kernels.

The use of small kernels allows designing a deeper architecture, besides having a positive effect against over fitting. We also investigated the use of intensity normalization as a pre-processing step, which though not common in CNN-based segmentation methods, proved together with data augmentation to be very effective for brain tumor segmentation. The proposed work uses CNN (Convolutional neural network) to identify the tumor and in this paper we have fostered a new transpire for segmentation of brain tumor in MRI using GLCM (Grey Level co-occurrence matrix) along with CNN technique to analyze the stage of

tumor that occurs in the patients. This paves way for sustainability for effective brain image screening, interpreting and sensitive detection using Magnetic Resonance Images.

INTRODUCTION

Among brain tumors, gliomas are the most common and aggressive, leading to a very short life expectancy in their highest grade. Thus, treatment planning is a key stage to improve the quality of life of oncological patients. Magnetic resonance imaging (MRI) is a widely used imaging technique to assess these tumors.

In this paper, we propose an automatic segmentation method based on Convolutional Neural Networks (CNN), exploring small 3x3

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com
International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 5, Special Issue 7, March 2018

kernels and a GLCM matrix. The use of small kernels allows designing a deeper architecture, besides having a positive effect against overfitting, given the fewer number of weights in the network.

CNN were used to achieve some breakthrough results and win well-known contests. The GLCM, which is a square matrix, can reveal certain properties about the spatial distribution of the gray-levels in the texture image. By using kernels, information of the neighborhood is taken into account, which is a useful source of context information. Thus, treatment planning is a key stage to improve the quality of life of oncological patients.

Convolutional Neural Network

CNN were used to achieve some breakthrough results and win well-known contests. The application of Convolutional layers consists in convolving a signal or an image with kernels to obtain feature maps. So, a unit in a feature map is connected to the previous layer through the weights of the kernels. The weights of the kernels are adapted during the training phase by back propagation, in order to enhance certain characteristics of the input. Since the kernels are shared among all units of the same feature maps, Convolutional layers have fewer weights to train than dense FC layers, making CNN easier to train and less prone to overfitting.

Important context of CNN

Initialization

It is important to achieve convergence. We use the Xavier initialization. With this, the activations and the gradients are maintained in controlled levels; otherwise back-propagated gradients could vanish or explode.

Activation Function

It is responsible for non-linearly transforming the data. Rectifier linear units, defined as were found to achieve better results than the more classical sigmoid, or hyperbolic tangent functions, and speed up training. However, imposing a constant can impair the gradient flowing and consequent adjustment of the weight. We hope with these limitations using a variant called leaky rectifier linear unit that introduces a small slope on the negative part of the function.

Pooling

It combines spatially nearby features in the feature maps. This combination of possibly redundant features makes the representation more compact and invariant to small image changes, such as insignificant details; it also decreases the computational load of the next stages. To join features it is more common to use max-pooling or average-pooling.

Regularization

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com
International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 5, Special Issue 7, March 2018

It is used to reduce overfitting. We use Dropout in the FC layers. In each training step, it removes nodes from the network with probability. In this way, the forces all nodes of the FC layers to learn better representations of the data, preventing nodes from co-adapting to each other. At test time, all nodes are used. Dropout can be seen as an ensemble of different networks and a form of bagging, since each network is trained with a portion of the training data.

Data Augmentation

It can be used to increase the size of training sets and reduce overfitting. Since the class of the patch is obtained by the central voxel, we restricted the data augmentation to rotating operations. Some authors also consider image translations, but for segmentation this could result in attributing a wrong class to the patch.

So, we increased our data set during training by generating new patches through the rotation of the original patch. In our proposal, we used angles multiple of 90, although another alternative will be evaluated.

Loss Function

It is the function to be minimized during training. We used the Categorical Cross-entropy, which represents the probabilistic predictions and is the target. In the next subsections, we discuss the architecture and training of our CNN.

Architecture

We aim at a reliable segmentation method; however, brain tumors present large variability in intra-tumor structures, which makes the segmentation a challenging problem.

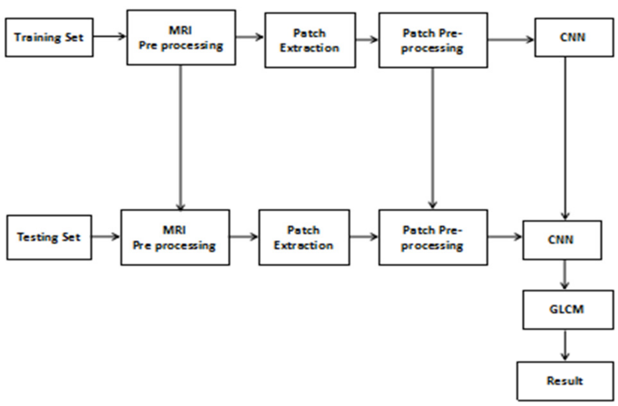
To reduce such complexity, we designed a CNN and tuned the intensity normalization transformation for each tumor grade—LGG and HGG. The architecture used for HGG is deeper than the one for LGG, because going deeper did not improve results in the latter.

Training

To train the CNN the loss function must be minimized, but it is highly non-linear. We use Stochastic Gradient Descent as an optimization algorithm, which takes steps proportionally to the negative of the gradient in the direction of local minima. Nevertheless, in regions of low curvature it can be slow.So, we also use Nesterov's Accelerated Momentum to accelerate the algorithm in those regions. The momentum is kept constant, while the learning rate was linearly decreased, after. Each epoch. We consider an epoch as a complete pass over all the training samples.

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com
International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 5, Special Issue 7, March 2018

BLOCK DIAGRAM



Gray-Level Co-occurrence Matrices (GLCMs)

The GLCM, which is a square matrix, can reveal certain properties about the spatial distribution of the gray-levels in the texture image. It shows how often a pixel value known as the reference pixel with the intensity value i occur in a specific relationship to a pixel value known as the neighbor pixel with the intensity value j. So, each element (i, j) of the matrix is the number of occurrences of the pair of pixel with value i and a pixel with value j which are at a distance d relative to each other.

The spatial relationship between two neighboring pixels can be specified in many ways with different offsets and angles, the default one being between a pixel and its immediate neighbor to its right. In the present work, four possible spatial relationships (00; 450; 900 and 1350) were specified and implemented. Grey Level Co-occurrence Matrices (GLCM) is one of the earliest techniques used for image texture analysis. The Gray Level Co-ocurrence Matrix (GLCM) method is a way of extracting second order statistical texture features. The approach has been used in a number of applications, Third and higher order textures consider the relationships among three or more pixels.

PRE-PROCESSING

MRI images are altered by the bias field distortion. This makes the intensity of the same tissues to vary across the image. This is not enough to ensure that the intensity distribution of a tissue type is in a similar intensity scale across different subjects for the same MRI sequence, which is an explicit or implicit assumption in most segmentation methods. In fact, it can vary even if the image of the same patient is acquired in the same scanner in different time points, or in the presence of pathology. In this intensity normalization method, a set of intensity landmarks are learned for each sequence from the training set. And are chosen for each MRI sequence represents the intensity at the percentile.

After training, the intensity normalization is accomplished by linearly transforming the original intensities between two landmarks into the corresponding learned landmarks. In this way, the histogram of each sequence is more similar across subjects after normalizing the MRI images. We compute the mean intensity value and standard

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com
International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 5, Special Issue 7, March 2018

deviation across all training patches extracted for each sequence. Then, we normalize the patches on each sequence to have zero mean.

In this intensity normalization method, aset of intensity landmarksare learned for each sequence from the training set. And are chosen for each MRI sequence as described represents the intensity at the percentile. After training, the intensity normalization is accomplished by linearly transforming the original intensities between two landmarks into the corresponding learned landmarks. In this way, the histogram of each sequence is more similar across subjects after normalizing the MRI images.

PATCH EXTRACTION

In the field of image processing, use of patches is not only simple and popular also results in effective approach to the proposed work. Let this processing of patches be applicable to enhance the image features like quality , colour intensity etc. There are exuberant challenges in enhancement of the image.

Instead of processing on the whole image at once, we propose a simple approach of segregating the image into patches and then applying image processing to enhance its features.

In the field of filtering a particular image there are lot of filtering approaches i.e. gabor filtering, erosion dilogen technquies are available. It made simple and easy when we workout with small element of the image that is patch.

PATCH PREPROCESSING

The Patch extracted from corrupted image have similar patch that exists from the same image. The size of patch is very low if we compare this with whole image (specifically size of patch will be 8x8 pixels). By applying patch based processing it is possible to enhance the given corrupted image efficiently as shown. The processing of these patches will be done through extraction of these patches and then rearranging them according to the euclidian distances between the patches. The processed resultant patches will be kept into the original corrupted image to reform enhanced smooth image.

There are different ways to interrelate the patches with each other one can arrange these patches as example NL means algorithm which involves weighted average of pixels with similar surroundings, clustering of patches and treat each set separately by using representative dictionary, using sparse representation of patches or pixels collecting the patches with similar properties in to a group perform sparsification on these groups extraction stage will be given as input to classifier.

Pituitary Brain Tumor

The pituitary gland is connected directly to part of the brain called the hypothalamus. The 100 MRI images of pituitary brain tumor have collected. The

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com
International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 5, Special Issue 7, March 2018

MR image acquisition protocol for each subject includes: T1-weighted contrast enhanced images.

Glioma Brain Tumor

The glioma tumor is the most common primary brain tumor. They occur in all age groups, with 75 to 84 year olds. The 100 T1-weighted contrast-enhanced MRI images of glioma brain glan has been collecetd.

Meningioma Brain Tumor

Meningiomas develop in meninges which is a membraine like structures surrounding spinal cord and brain. The T1- weighetd contrast-enhanced MRI images of 100 patients has collected.

All the 300 MRI images of pituitary, glioma & meningioma brain tumor has been collecetd from SKN Hospital in Pune.

Tumor Segmentation

The very first step in the proposed system is to separate the tumor region from the rest of the image i.e. separation ofabnormal tissues and normal tissues. Many segmentation techniques has been studied and implemented in past fewyears for brain tumor detection. In our research, we have used watershed transform method for segmentation of tumor.

The advantages of this method are, the resulting boundaries form closed and connected regions. This method is veryeasy to implement and simple to understand. The watershed segmentation is well known edge based segmentationalgorithm. Watershed means a basin-like landform defined by highpoints & ridgelines that move down into lowerelevations and small valleys. In geographically, the line separating two catchment basins is called aswatershed line. The water or rain falls on both side of watershed line will flow in to the same lake or dam.

The concepthas used in image processing for solving segmentation problems. The watershed is useful for the value of higherintensity. The technique for segmenting the digital images that use a type of region growing method based on an imagegradient. Gradient descent describes segmented regions.

Feature Extraction

To connote any image big pack of information is needed. This information consumes lots of space in memory. Thenumber of features is extracted from an image.

These features provide relevant information about the image. Theextracted features are provided as an input to the classifier for classification.

Magnetic Resonance Imaging

A magnetic resonance imaging instrument (MRI Scanner)uses powerful magnets to polarize and excite hydrogennuclei i.e. proton in water molecules in human tissue,producing a detectable signal which is spatially encoded,resulting in images of the body. MRI uses threeelectromagnetic fields. A very strong static magnetic field to polarize thehydrogen nuclei, called the static field. A weaker time varying field(s) for spatial encodingcalled the gradient field. A weak radio frequency field for manipulation ofhydrogen nuclei to produce measurable signalsCollected through RF antenna.

Class I (Astrocytoma)

The patient was a 35-year-old man; MR demonstrates anarea of mixed signal intensity on proton density (PD) andT2-weighted (T2) images in a left occipital region.Contrast enhancement shows the lesion to contain cysticelements.

Class II (Meningioma)

The patient was a 75-year-old man who had an 8 – 10month history of progressive difficulty walking. He hadnoted some left lower extremity weakness and somedifficulty with memory and concentration. He was alertand oriented, but had slow and hesitating speech. He couldrecall only 1 of 3 objects at five minutes.

Class III (Metastatic broncho genic carcinoma)

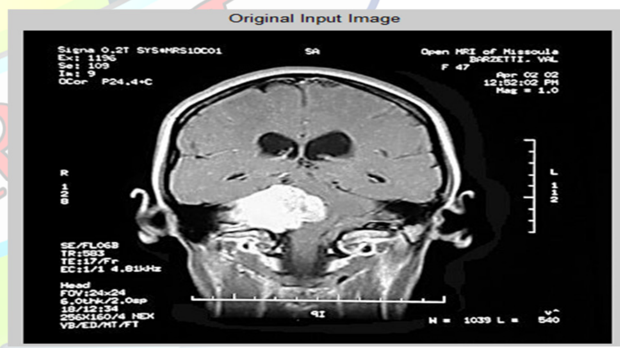
This 42 year old woman with a long history of tobacco usebegan having headaches one month before these imageswere obtained. Brain images show a large mass withsurrounding edema, and compression of adjacent midbrainstructures. The MR demonstrates the tumor as an area ofhigh signal intensity on proton density (PD) and T2-weighted (T2) images in a large left temporal region.

Class IV (Sarcoma)

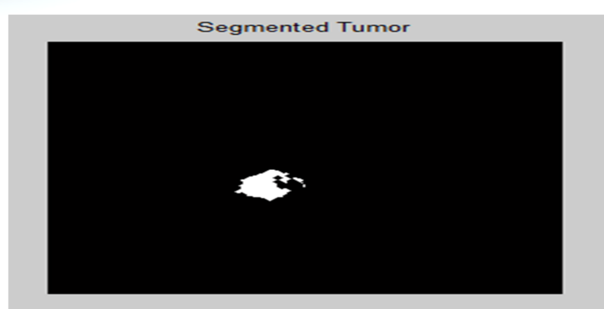
The patient was a 22 year old man who was admitted forresection of Ewing's sarcoma (peripheral/primitiveneuroepithelial tumor- PNET). Vaguely described visualdifficulty was noted retrospectively to have begunapproximately one month prior to admission.we tried to classify the four different classes of tumor types such as Astrocytoma, Meningioma, Metastatic broncho genic carcinoma, and Sarcoma.

RESULT

INPUT IMAGE

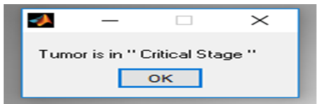


OUTPUT IMAGE



ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 5, Special Issue 7, March 2018



CONCLUSION

Segmentation of images by defining anatomical structures and regions of interest has an essential role in many medical imaging applications. A variety of techniques has been proposed to solve the problems associated with feature extraction, segmentation and detection of tumor, which are significant stages in an automatic diagnosis system. Image segmentation is an indispensable part of the tumor identification, particularly during analysis of Magnetic Resonance (MR) Images. Various methods proposed in the literature have met with only limited success due to overlapping intensity distributions of healthy tissue, tumor and surrounding edema. In order to achieve better results in detection process, it is intend to utilize lifting Grey Level Co-occurrence Matrix (GLCM) and Convolutional Neural Network (CNN) for classifying whether the input image is normal one or tumor image and also to detect the stages of tumor. In the proposed method, the following are the major steps, which include Pre-processing, Patch extraction and Tumor classification to find whether the input MR Image is tumorous or non-tumorous.The proposed techniquewill also be implemented using MATLAB and performance of this technique will be analyzed to prove the effectiveness of the algorithm.

REFERENCES

[1] S.Bauer *et al.*, “A survey of MRI-based medical image analysis for brain tumor studies,” *Phys. Med. Biol.*, vol. 58, no. 13, pp. 97–129, 2013.

[2] D. N. Louis *et al.*, “The 2007 who classification of tumours of the central nervous system,” *Acta Neuropathologica*, vol. 114, no. 2, pp. 97–109, 2007.

[3] E. G. Van Meir *et al.*, “Exciting new advances in neuro-oncology: The avenue to a cure for malignant glioma,” *CA, Cancer J. Clinicians*, vol. 60, no. 3, pp. 166–193, 2010.G.Tabatabai *et al.*, “Molecular diagnostics of gliomas: The clinical perspective,” *Acta Neuropathologica*, vol. 120, no. 5, pp. 585–592, 2010

[4] B.Menze *et al.*, “The multimodal brain tumor image segmentation benchmark (BRATS),” *IEEE Trans. Med. Imag.*, vol. 34, no. 10, pp. 1993–2024, Oct. 2015.N. J. Tustison *et al.*, “N4ITK: Improved n3 bias correction,” *IEEETrans. Med. Imag.*, vol. 29, no. 6, pp. 1310–1320, Jun. 2010.

[5] L. G. Nyúl, J. K. Udupa, and X. Zhang, “New variants of a method of MRI scale standardization,” *IEEE Trans. Med. Imag.*, vol. 19, no. 2, pp. 143–150, Feb. 2000.

[6] M. Prastawa *et al.*, “A brain tumor segmentation framework based on outlier detection,” *Med. Image Anal.*, vol. 8, no. 3, pp. 275–283, 2004.

[7] B. H. Menze *et al.*, “A generative model for brain tumor segmentation in multi-modal images,” in *Medical Image Computing and Comput.-Assisted Intervention-MICCAI 2010*. New York: Springer, 2010, pp.151–159.

[8] A. Gooya *et al.*, “GLISTR: Glioma image segmentation and registration,” *IEEE Trans. Med. Imag.*, vol. 31, no. 10, pp. 1941–1954, Oct. 2010

[9] Sérgio Pereira*, Adriano Pinto, Victor Alves, and Carlos A. Silva* ”Brain tumor Segmentation using Convolutional neural network in MRI Images”. In MAY 2016.