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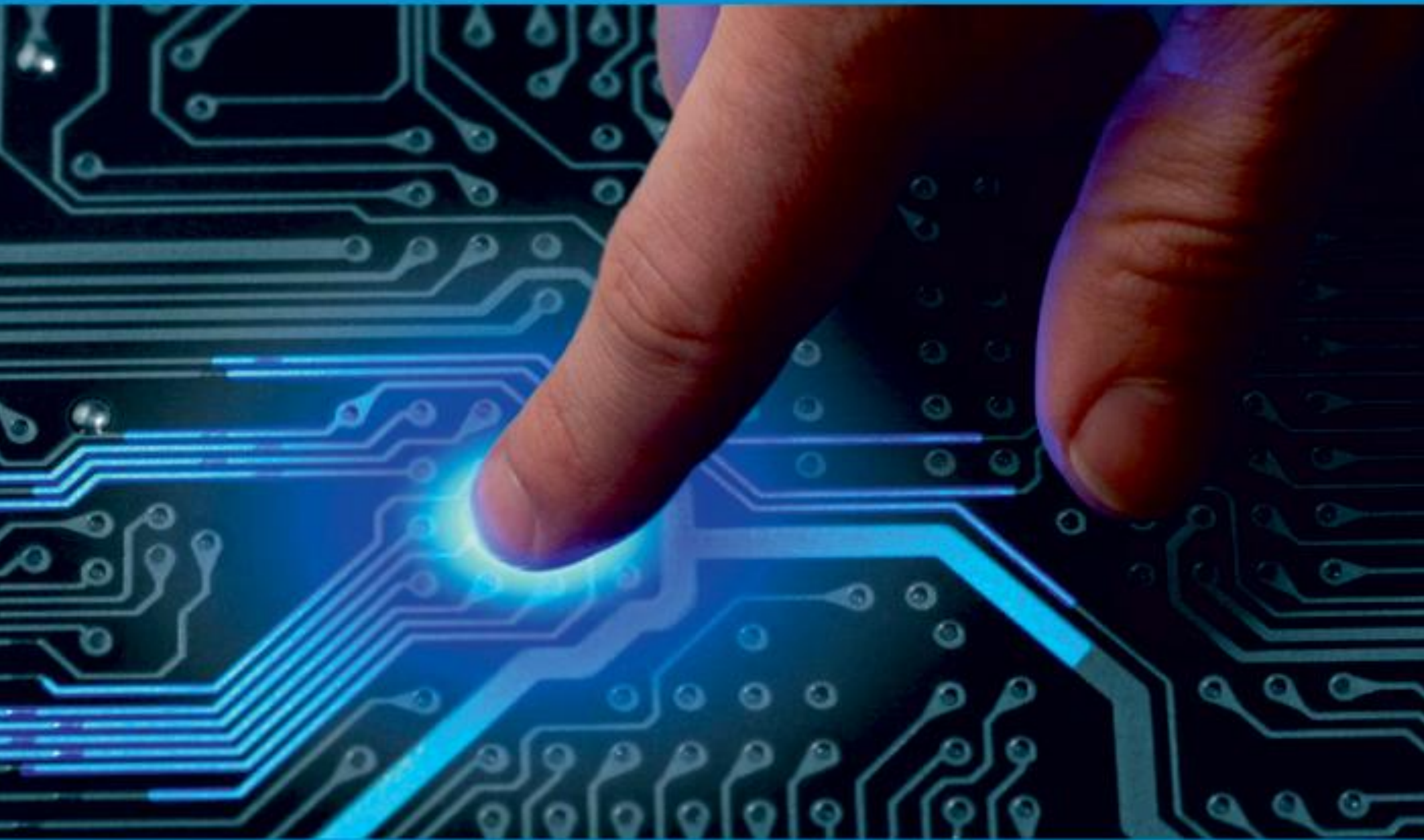

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Segmenting Brain Cancer Tissue from MRI Using Optimised Deep Neural Network Model

Mrs.Malligeswari, Tadisetty Chenchu Babu, Chevuri Siva Sankar

Assistant Professor, Department of Electronics and Communication Engineering, S.K.R Engineering College ,Chennai , Tamil Nadu, India

Department of Electronics and Communication Engineering, S.K.R Engineering College, Chennai, Tamil Nadu, India

Department of Electronics and Communication Engineering, S.K.R Engineering College, Chennai, Tamil Nadu, India

ABSTRACT: Brain tumors are very hazardous for a patient whether its malignant or benign syndrome, which drags to a minutely min uscular life cycle in the highest degree. So the, treatment is very consequential way to boost up the life of expectancy. More than one convolution layers with deep neural network is utilized for finding feature in neoplasm image. The utilization of diminutive kernels (3*3 or 5*5 size) sanctions designing a deeper design, besides having a positive impact against over fitting. The goal is classification with segmentation of tumor part with the help of convolutional neural network and K means clustering Algorithm. In this project the input to the system is considered as brain scanned MRI image.

I. INTRODUCTION

Medical Image processing is a consequential filed of research utilized for the better Treatment of health issues. Encephalon tumor is very mundane and truculent illness, so the surgery is very crucial part for medicos and to abstract the tumor is compulsory. Radiologists use MRI scans to diagnose a sundry condition, from torn ligaments to tumors. MRI are very subsidiary for examining the encephalon and spinal cord. This proposed work deals with the Encephalon tumor segmentation along with its relegation utilizing Convolution Neural Network. Before performing segmentation process of given MRI image, we have to classify whether the tumor is present or not then we will do segmentation. (a) And (b) images shows the normal and abnormal (tumorous) brain MRI.

BRAIN TUMOR is caused by the uncontrolled magnification of tissue in the brain or central spine that can disrupt proper brain function. Primary brain tumors originate from cells within the brain and secondary (metastatic) brain tumors begin in another part of the body and then spread to the brain. Brain tumors can be cancerous (malignant) or non-cancerous (benign). There are over 120 brain tumor relegations defined by the WHO, predicated on the tumor cell type and location. They are graded based on the cells where they arise, and a number ranging from I-IV. Grades I and II are considered as lower grade tumors, and III and IV are considered as higher grade tumors. Brain tumors can be life-threatening and thus precise diagnosis and necessary treatment is vital for a patient. In the pathology lab, tumor tissue analysis is carried out by utilizing microscopic analysis such as biopsy and electronic modalities such as CT, Ultrasound, MRI etc.

Among all electronic modalities Magnetic Resonance Imaging (MRI) is one of the most used and popular for brain tumor diagnosis. It takes a high resolution and high contrast images of the brain in the axial, coronal and sagittal orientation providing a three-dimensional assessment of the lesion. In this research study, an automated approach has been proposed where MRI gray-scale images were incorporated for brain tumor detection. Brain tumor images were taken as input and medical image processing techniques such as preprocessing and post-processing were incorporated to identify the tumor region only. The pre-processing includes enhancement, filter operation, and segmentation and post processing includes feature extraction and identification. However, if the tumor is in the brain stem or certain other areas, the surgeon may not be able to remove tissue from the tumor without harming normal brain tissue. In this case, the doctor uses MRI, CT, or other imaging tests to learn as much as possible about the brain tumor.

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II. LITERATURE SURVEY

Researchers like **Benson et al., (2015)** has researched thatHuman brain is the most complex and mysterious part of human body. Many complex functions are controlled by brain. Brain imaging is a widely applicable method for diagnosing many brain abnormalities such as brain tumor, stroke, paralysis etc. Magnetic Resonance Imaging (MRI) is one of the methods used for brain imaging. It is used for analysing internal structures in detail. Brain tumor is an abnormal mass of tissue in which cells grow and multiply uncontrollably, seemingly unchecked by the mechanisms that control normal cells. The aim of this paper is to extract tumor region from the brain MRI image using watershed algorithm based on different feature combinations such as colour, edge, orientation and texture. The results are compared with the ground truth images. Here we used marker based watershed algorithm for extracting tumored region and Dice and Tanimoto coefficients are used for comparison of the results. The method proposed here is found to be producing a promising result.Tumor identification and segmentation from MRI brain images are the most challenging task for a clinician. In this work marker based watershed segmentation algorithm is implemented with different combinations of features. Each combination produces prominent results. From the table, it is evident that the color and orientation features cannot be considered for the watershed segmentation purpose. All other combinations yield the same result. By comparing the other methods, the proposed method using combination of features gives better results. Here we manually identified the markers for the algorithm. Future work is to identify the markers automatically and segment the tumored area based on the automatically identified markers. While the other researcher named **Meiyan Huang et al., (2014)**found thatBrain tumor segmentation is an important procedure for early tumor diagnosis and radiotherapy planning. Although numerous brain tumor segmentation methods have been presented, enhancing tumor segmentation methods is still challenging because brain tumor MRI images exhibit complex characteristics, such as high diversity in tumor appearance and ambiguous tumor boundaries. To address this problem, we propose a novel automatic tumor segmentation method for MRI images. This method treats tumor segmentation as a classification problem. Additionally, the local independent projection-based classification (LIPC) method is used to classify each voxel into different classes. A novel classification framework is derived by introducing the local independent projection into the classical classification model. Locality is important in the calculation of local independent projections for LIPC. Locality is also considered in determining whether local anchor embedding is more applicable in solving linear projection weights compared with other coding methods. Moreover, LIPC considers the data distribution of different classes by learning a softmax regression model, which can further improve classification performance. In this study, 80 brain tumor MRI images with ground truth data are used as training data and 40 images without ground truth data are used as testing data. The segmentation results of testing data are evaluated by an online evaluation tool. The average dice similarities of the proposed method for segmenting complete tumor, tumor core, and contrast-enhancing tumor on real patient data are 0.84, 0.685, and 0.585, respectively. These results are comparable to other state-of-the-art methods.

III. PROPOSED METHOD

Initially, the MRI brain image is taken as an input for convolutional neural network system. System will classify there is tumor or not. if there is tumor image will go for segmentation part. K means clustering algorithm applied on output image and tumor part will be segmented. If there is no tumor then directly it will indicate normal brain.

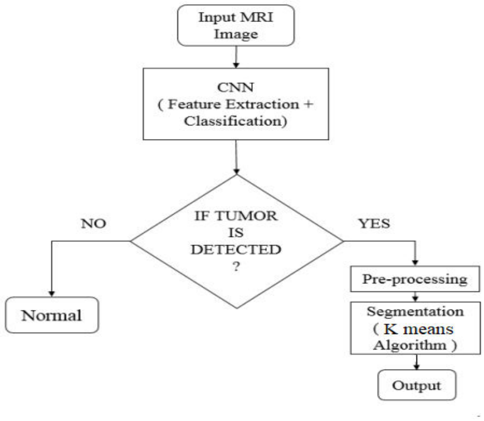

Fig 1 Flowchart

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HARDWARE DESCRIPTION

CNN

Convolutional Neural Networks (CNN) are everywhere. It is arguably the most popular deep learning architecture. The recent surge of interest in deep learning is due to the immense popularity and effectiveness of convnets. The interest in CNN started with AlexNet in 2012 and it has grown exponentially ever since. In just three years, researchers progressed from 8 layer AlexNet to 152 layer ResNet. CNN is now the go-to model on every image related problem. In terms of accuracy they blow competition out of the water. It is also successfully applied to recommender systems, natural language processing and more. The main advantage of CNN compared to its predecessors is that it automatically detects the important features without any human supervision. For example, given many pictures of cats and dogs it learns distinctive features for each class by itself. CNN is also computationally efficient. It uses special convolution and pooling operations and performs parameter sharing. This enables CNN models to run on any device, making them universally attractive. All in all this sounds like pure magic. We are dealing with a very powerful and efficient model which performs automatic feature extraction to achieve superhuman accuracy (yes CNN models now do image classification better than humans). Hopefully this article will help us uncover the secrets of this remarkable technique.

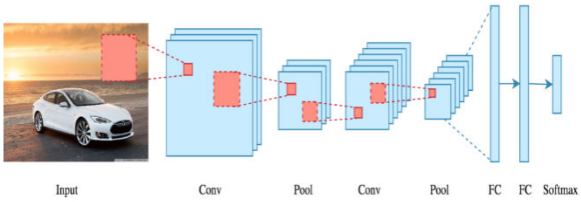

Fig 2 CNN Model Architecture

CNNS in finger-vein scenario

In recent years, applications of deep-learning-based methods, such as CNN, have been introduced in vein-based recognition scenario.A CNN is a multilayer perceptron (MLP) network with a special topology containing more than one hidden layer .CNNs are primarily used for object recognition in image processing, handwritten character recognition and speech recognition, as they automatically extract discriminative featuresinside their layers from raw input information, without any specific normalization. This kind of model is advantageous for input data with an inner structure like images, and where invariant features have to be discovered. One of the main interest for using CNNs is to avoid hand-designed input features, which may not have been derived by considering the general problems. Following subsections will provide detailed description of different layers of a CNN.

Template generation

Bigger images usually lead to a larger CNN with more hidden layers. Hence, in order to have a feasible size network, the images are first resized into 65 × 153. In our approach, the training and testing templates of our network are either generated by selecting the images from a single session, as proposed by existing state-of-the-art methods, or by selecting a combination of images from all available sessions.

CNN training

The generated templates are passed through the designed CNN and a set of very low-level features are extracted in the first hidden layer. The network gradually builds up over these low-level features in the subsequent convolutional layers, in order to create a set of high-level features for the fully connected layer. For our experiments we have considered each finger of every person as a separate class.

Median filter

The median filter is a nonlinear digital filtering technique, often used to remove noise. Such noise reduction is a typical pre-processing step to improve the results of later processing (for example, edge detection on an image). Median

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filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise.

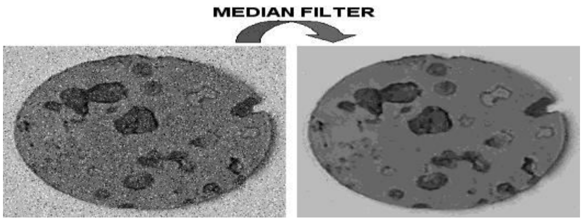

Fig 3 Median Filter

K-Means Clustering

K-Means clustering is a method of vector quantization, originally from signal processing, that is popular for cluster analysis in data mining. k-means clustering aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster. This results in a partitioning of the data space into Voronoi cells.The problem is computationally difficult (NP-hard); however, there are efficient heuristic algorithms that are commonly employed and converge quickly to a local optimum. These are usually like the expectation-maximization algorithm for mixtures of Gaussian distributions via an iterative refinement approach employed by both algorithms. Additionally, they both use cluster centers to model the data; however, k-means clustering tends to find clusters of comparable spatial extent, while the expectation-maximization mechanism allows clusters to have different shapes.

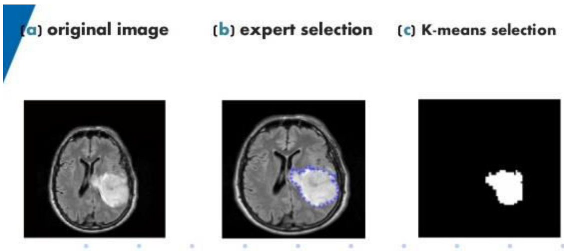

Fig 4 Grayscale image segmentation

SOFTWARE DESCRIPTION

MATLAB

MATLAB is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation. It is an interactive system whose basic data element is an array that does not require dimensioning. This allows you to solve many technical computing problems, especially those with matrix and vector formulations, in a fraction of the time it would take to write a program in a scalar noninteractive language such as C or Fortran.

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V. RESULTS AND DISCUSSION

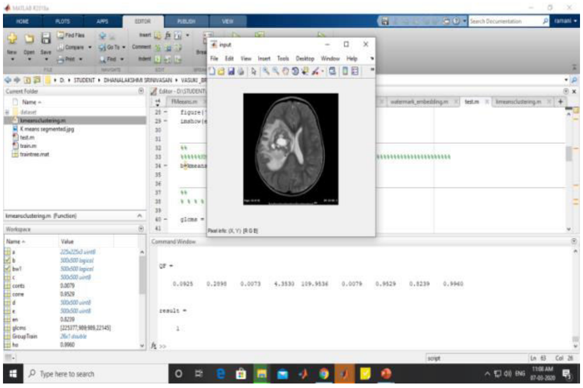

Fig 5 Input image

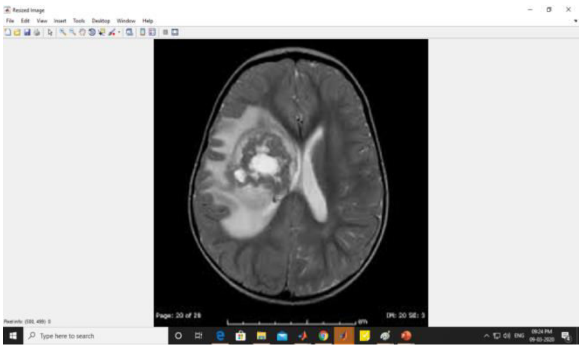

Fig 6 Resized Image

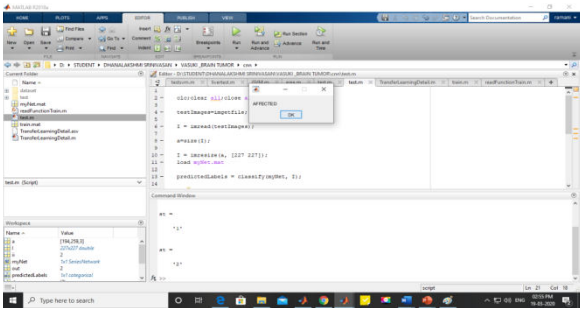

Fig 7 CNN Result

Fig 8 Result obtained through Median Filter

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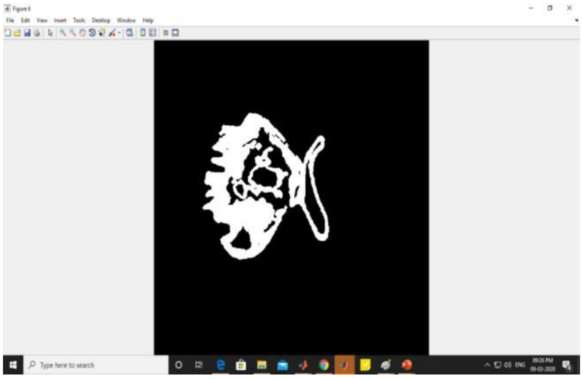

Fig 9 Segmentation picture

VI. CONCLUSION

The main idea behind this research work is to prototype economical automatic brain tumor classification and segmentation with high accuracy and low complication. Brain tumor segmentation part is done using K means clustering algorithm. K means clustering algorithm gives very good segmentation results. CNN classifies input image in two classes as normal brain and tumorous brain. Total 50 images of the brain have been considered as input dataset for training. In future the algorithm could be modified to identify the types of tumor (i.e. Oligodraglioma, Meningioma, Optic Glioma, Pineal Region tumors).

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