"AN EFFICIENT DIGITAL SUPPORT SYSTEM FOR DIAGNOSING BRAIN TUMOR"

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Abstract – Image segmentation plays a crucial role in many medical imaging applications, especially in medical image categorization. Because of this, correct features are extracting from a segmented representation. In addition, support vector machine is used for classification works with feature extraction, an extra step is necessary to select appropriate features among a large feature set. As feature selection is important for medical data mining to reduce processing time and to increase classification accuracy. According to the experiments in which the Segmentation model is used in the classification part, dissimilar diseases such as cancer, eye sickness, skin, brain tumor especially, breast cancer can be diagnosed. In addition, the severity of diseases can be determined by the use of the image classifier. In this section, according to the type of diseases, the methods of segmentation and feature extraction are described. Image segmentation and its performance evaluation are vital aspects in image dispensation because of the complexity of the medical images; segmentation of medical descriptions remains a challenging predicament. The Segmentation model can be used as an approach for segmentation of different diseases such as breast cancer renal calculi and, especially, brain tumor.

Key Words: Brain tumour, Median filter, Segmentation and neural network.

1. INTRODUCTION

With the advancement in the technology the concept of image processing play an important role in medical field and with deep learning we get better promising results in the different field, for example, speech recognition, handwritten character recognition, image classification, image detection and segmentation and disease detection[1]. Brain Tumor Symptoms: Symptoms (signs) of benign brain tumors often are not specific. The following is a list of symptoms that, alone or combined, can be caused by benign brain tumors; unfortunately, these symptoms can occur in many other diseases: vision problems ,hearing problems ,balance problems ,changes in mental ability (for example, concentration, memory, speech), seizures, muscle jerking, change in sense of smell ,nausea/vomiting, facial paralysis,headaches,numbness in extremities. The research is based on the automatic detection of brain tumor and the classification is done by using Support vector machine.

In this paper, I am going to analysis and implement the Brain Cancer detection. This is very serious disease causing deaths of many individuals. The detection and classification system must be available so that it can be diagnosed at early stages. Cancer classification has been one of the most challenging tasks in clinical diagnosis. At present cancer classification is done mainly by looking through the cells' by using morphological differences, segmentation methods, and K-NN classification that does not always give a clear distinction of cancer subtypes. Unfortunately, this may have a significant impact on the final outcome of whether a patient could be cured effectively or not. This research deals with such a system which uses computer based procedures to detect tumor blocks and classify the type of tumor using Machine learning (support vector machine)Algorithm for MRI images of different patients. Different image processing techniques such as image preprocessing for noise filtering with median filter then image segmentation, morphological operation and feature extraction classification using support vector machine are used for detection of the brain tumor in the MRI images of the cancer affected patients. Medical Image Processing is the fast growing and challenging field now days. Medical Image techniques are used for Medical diagnosis. Brain tumor is a serious life threatening disease. Detecting Brain tumor using Image Processing techniques involves four stages namely Image Pre-Processing, Image segmentation, Feature Extraction, and Classification. Image processing and neural network techniques are used to improve the performance of detecting and classifying brain tumor in MRI images.

The brain is the body organ composed of nerve cells and supportive tissues like glial cells and meninges – there are three major parts – they control your activity like breathing (brain stem), activity like moving muscles to walk (cerebellum) and your senses like sight and our memory, emotions, thinking and personality (cerebrum). A brain tumor is a collection, or mass, of abnormal cells in your brain. Your skull, which encloses your brain, is very rigid. Any growth inside such a restricted space can cause problems. Brain tumors can be cancerous (malignant) or noncancerous (benign). When benign or malignant tumors grow, they can cause the pressure inside your skull to increase. This can cause brain damage, and it can be life-threatening.so an early detection of tumor is required and for that a reliable technique is required, thus we use digital image processing methods with support vector machine.

2. PROBLEM IDENTIFICATION

After reading various research papers, the conclusion of all these papers is the tumour detection accuracy is achieved by using various complex approaches for detecting the goal of detecting tumour by mri image understanding, color/grey-level/texture/shape can help locate interesting zones/objects. Though, a partition based on such criteria will often contain too many regions to be exploitable, interesting objects hence being split into several regions.

Segmentation is the process of automatically separating an image into different regions in a fashion that mimics the human visual system. It is therefore a broad term that is highly dependent on the application at hand, e.g. one might want to segment each object individually, groups of objects, parts of objects, etc. In order to segment a particular image, one must identify the projected result before a set of rules can be chosen to target this goal. There are various segmentation-based approaches proposed to express the object and its spatial information. Segmentation is performed to recognize objects from the image using features. A feature can be intensity value, edge, corners, texture, shape, etc. The selection of features can be depended on requirements given by user. The human eye uses low-level information such as the presence of boundaries, regions of different intensity or colours, brightness and texture and hence selects suitable feature accordingly. The intensity value is the simplest feature of image. The classification of image is directly applied on the intensity value of pixels.

3. PROPOSED WORK

In this paper first we capture the image of MRI

Then preprocessing of image will take place and then median filtering, edge detection, segmentation and classification using cnn for detection.

3.1 INPUT a raw image

For image data set, Google MRI images are used for the detection but we considered the high resolution images for better accuracy and t he image can be further utilized for processing; Captured image is given to as input.

Figure 1

3.2 Preprocessing of Image

Like the mean filter, the median filter considers each pixel in the image in turn and looks at its nearby neighbors to decide whether or not it is representative of its surroundings. Instead of simply replacing the pixel value with the mean of neighboring pixel values, it replaces it with the median of those values. The median [5] is calculated by first sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value. (If the neighborhood under consideration contains an even number of pixels, the average of the two middle pixel values is used.) Figure 2 illustrates an example calculation.

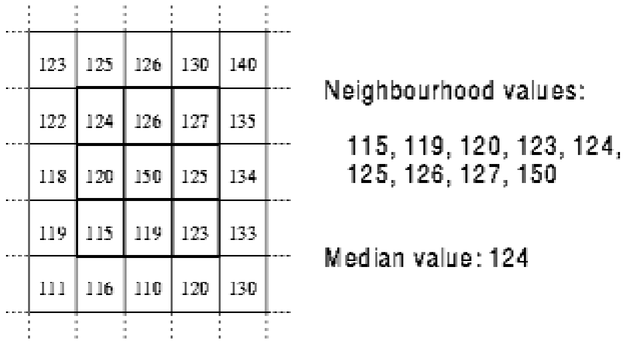

Figure: 2

3.3 Image segmentation and morphological operations

Segmentation subdivides an image into its constituent regions or objects. Segmentation is a process of grouping together pixels that have similar attributes. Image Segmentation is the process of partitioning an image into non-intersecting regions such that each region is homogeneous and the union of no two adjacent regions is homogeneous[3]. Segmentation is typically associated with pattern recognition problems. It is considered the first phase of a pattern recognition process and is sometimes also referred to as object isolation.

Converting a greyscale image to monochrome is a common image processing task. Otsu's method[7], named after its inventor Nobuyuki Otsu, is one of many binarization algorithms as shown in figure 2.

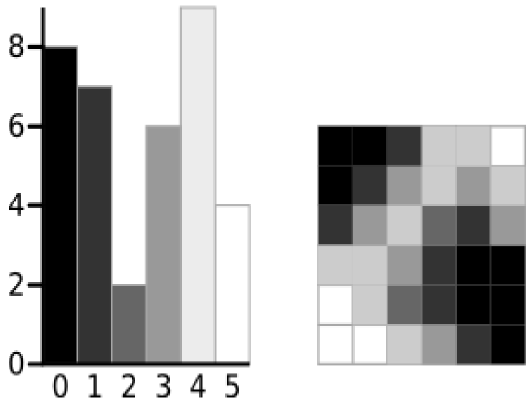

Figure:3

As otsu thresholding[6] play an important role in image segmentation and its is an automatic thresholding that give much better result as compared with the other segmentation algorithms. That's why we use automatic otsu thresholding algorithm in our work. Also we use morphological operations for dilation erosion and extraction the main infected area only so for that we use mathematically morphological operations also in our work

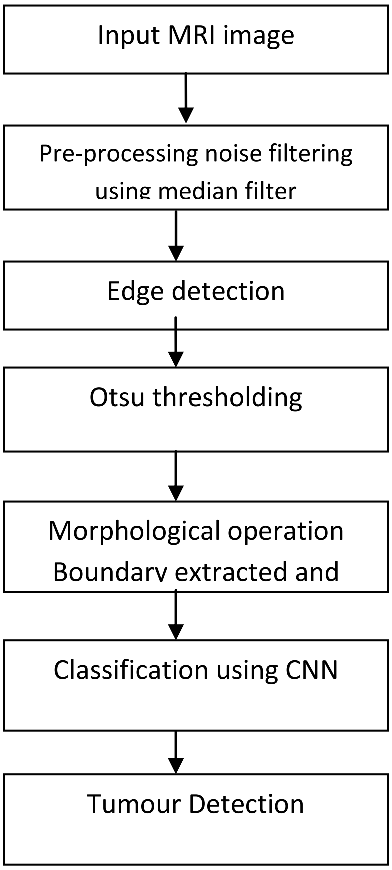

Figure :4

The identification of objects within an image can be a very difficult task. One way to simplify the problem is to change the grayscale image into a binary image, in which each pixel is restricted to a value of either 0 or 1. The techniques used on these binary images go by such names as: blob analysis, connectivity analysis, and morphological image processing (from the Greek word morphē, meaning shape or form). The foundation of morphological processing is in the mathematically rigorous field of set theory; however, this level of sophistication is seldom needed. Most morphological algorithms are simple logic operations and very ad hoc. As shown in the figure below

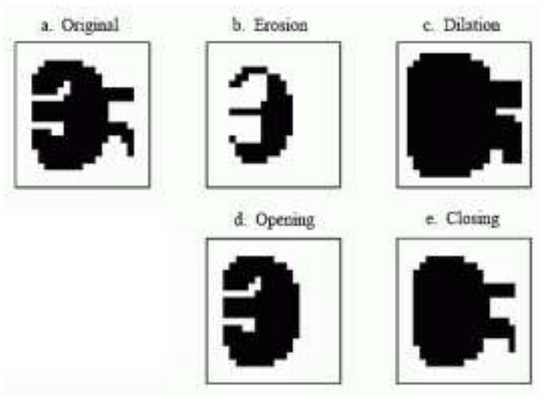

Figure: 5

3.4 Classification using CNN

A convolutional neural network (CNN)[8][9][10] is a special architecture of artificial neural networks, proposed by Yann LeCun in 1988. CNN uses some features of the visual cortex. One of the most popular uses of this architecture is image classification. For example Facebook uses CNN for automatic tagging algorithms, Amazon—for generating product recommendations and Google—for search through among users' photos. ConvNet has two parts: feature learning (Conv, Relu,and Pool) and classification(FC and softmax layer).

There are four main operations in the ConvNet shown in Figure 5(a) below:

Convolution- Convolution networks are composed of an input layer, an output layer, and one or more hidden layers. A convolution network is different than a regular neural network in that the neurons in its layers are arranged in three dimensions (width, height, and depth dimensions). This allows the CNN to transform an input volume in three dimensions to an output volume. The hidden layers are a combination of convolution layers, pooling layers, normalization layers, and fully connected layers. CNNs use multiple conv layers to filter input volumes to greater levels of abstraction. CNNs improve their detection capability for unusually placed objects by using pooling layers for limited translation and rotation invariance. Pooling also allows for the usage of more convolutional layers by reducing memory consumption. Normalization layers are used to normalize over local input regions by moving all inputs in a layer towards a mean of zero and variance of one. Other regularization techniques such as batch normalization, where we normalize across the activations for the entire batch, or dropout, where we ignore randomly chosen neurons during the training process, can also be used. Fully-connected layers have neurons that are functionally similar to convolution layers (compute dot products) but are different in that they are connected to all activations in the previous layer.

ReLU Layer- The rectifier function is an activation function f(x) = Max(0, x) which can be used by neurons just like any other activation function, a node using the rectifier activation function is called a ReLu node

Pooling or Sub Sampling- Convolutional networks may include local or global pooling layers, which combine the outputs of neuron clusters at one layer into a single neuron in the nextlayer. For example, max pooling uses the maximum value from each of a cluster of neurons at the prior layer

Classification (Fully Connected Layer)- Finally, after several convolutional and max pooling layers, the high-level reasoning in the neural network is done via fully connected layers. Neurons in a fully connected layer have connections to all activations in the previous layer, as seen in regular neural networks

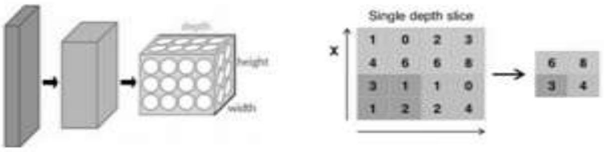

Figure 6

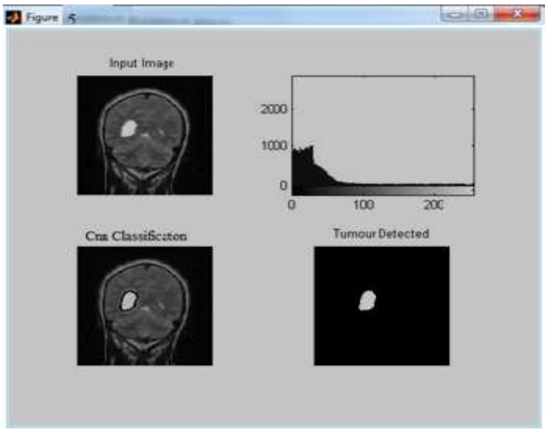

Figure 7

4. CONCLUSION

The Objective of this paper is to review the idea behind making an automatic System that use deep convolution neural network. Studying and resolving all the issues regarding Algorithms used for brain tumour detection in previous few years. The algorithm used in this paper not only accelerates the process but also increases the probability of detecting the tumour and extraction of tumour under certain set of constraints. As classification performs an important role in tumour detection thus we are focusing on the number of iterations (Hidden layers). The result of proposed method shows higher accuracy of infected region removal. Tumour identification system plays an important role in early detection of tumour and thus it saves the life.

The work has been carried out by varying size of window to visualize effect of window size on proposed idea. From results, one infers that:

- Smaller window size preserves edge information in segmented image
- As window size increases, smoothness of area considered by that window increases and sharpness of area decreases
- It also affects the values of moment computed for feature vector due to averaging of pixels of a window
- As window size increases, the noise tolerance of proposed algorithm increases
- As window size increases, the computational time of proposed algorithm increases

The pixel based classification consists of pixel values whose size depends on window size. In 2x2, 3x3 and 4x4 window size, the size respectively. The 2x2 window size may not have sufficient data to compute pixel and 4x4 window sizes has sufficient data, better for noise strength but its execution time is more. Hence, the trade-off can be decided to choose 3x3 window size for better results.

The study of pixel based shows that Statistical moment has almost same performance in quality but Statistical moment has required very less computation time. It also has minimum misclassification rate mostly in both the cases; with noise and without noise. Future work of this scheme is concentrating on the other features of the image for segmentation.

REFERENCES

1. Heba mohsen et al “Classification using deep learning neural networks for brain tumors”, Future computing and Informatics journal 3, 2018 P.No-68-71.Elsevier.

2. Ali et al “Review of MRI-based brain tumor image segmentation using deep learning methods” 12th International Conference on Application of Fuzzy Systems and Soft Computing, ICAFS 2016, 29-30 August 2016, Vienna, Austria, Procedia Computer Science 102 (2016) 317 – 324,Elsevier

3. Orlando, J, Tobias & Rui Seara (2002) “Image Segmentation by Histogram Thresholding Using Fuzzy Sets”, IEEE Transactions on Image Processing, Vol.11, No.12, 1457-1465.

4. Punam Thakare (2011) “A Study of Image Segmentation and Edge Detection Techniques”, International Journal on Computer Science and Engineering, Vol 3, No.2, 899-904.

5. Rafael C. Gonzalez, Richard E. Woods & Steven L. Eddins (2004) Digital Image Processing Using MATLAB, Pearson Education Ptd. Ltd, Singapore.

6. Zhao Yu quian ,Gui Wei Hua ,Chen Zhen Cheng,Tang Jing tian,Li Ling Yun,” Medical Images Edge detection Based on mathematical Morphology”, Proceedings of the 2005 IEEE.

7. Yu, X, Bui, T.D. & et al. (1994) “Robust Estimation for Range Image Segmentation and Reconstruction”, IEEE trans. Pattern Analysis and Machine Intelligence, 16 (5), 530-538.

8. S.Lakshmi,Dr. V .Sankaranarayanan,” A study of Edge Detection Techniques for Segmention Computing Approaches”, IJCA special issue on “ Computer Aided Soft Computing Techniques for imaging and Biomedical Applications”CASCT,2016

9. J. Koplowitz “On the Edge Location Error for Local Maximum and Zero-Crossing Edge Detectors”, IEEE Trans. Pattern Analysis and Machine Intelligence, vol.16, pg-12, Dec.1994.

10. De Angelis L M. Brain Tumors. N. Engl. J. Med. 2001; 344:114-23.

11. Deimling A. Gliomas. Recent Results in Cancer Research vol 171. Berlin: Springer; 2009.

12. Stupp R. Malignant glioma: ESMO clinical recommendations for diagnosis, treatment and follow-up. Ann Oncol 2007; 18(Suppl 2):69-70.

13. Drevelegas A and Papanikolou N. Imaging modalities in brain tumors Imaging of Brain Tumors with Histological Correlations. Berlin: Springer; 2011; chapter 2:13-34.

14. yatendra kashyap et al "advanced-automatic-brain-tumor-detection-system-using-deep-convolutional-neural-network" IJMTER,September 2108

15. Menze B, et al. The Multimodal brain tumor image segmentation benchmark (brats). IEEE Trans Med Imaging 2015; 34(10):1993-2024.