



A STUDY OF DETECTING AND CLASSIFYING BRAIN TUMOR AS NORMAL AND ABNORMAL TUMORS IN MRI IMAGES

CANDIDATE NAME= SATYAM KACHHTI

DESIGNATION= RESEARCH SCHOLAR SUNRISE UNIVERSITY ALWAR

GUIDE NAME= DR. VIRENDRA SINGH

DESIGNATION= ASSISTANT PROFESSOR

SUNRISE UNIVERSITY ALWAR RAJASTHAN

ABSTRACT

The primary goal of this study is to diagnose brain tumors based on MRI scans. After a tumor has been successfully located, a computer-aided diagnosis (CAD) system is developed using artificial intelligence methods so that a diagnosis may be made automatically. Pre-screening the MRI images with such CAD systems is necessary since brain tumors are so common in humans. Traditional methods of diagnosing brain tumors are more time-consuming, and their findings have now become mostly irrelevant. The project made use of a massive database of MRI scans, but only the most relevant scans were considered by applying a filter based on the tumor's textual and spectroscopic characteristics. Brain tumors may be detected early with the use of MRI scans so that patients can get the therapy they need. The MRI characteristics are extracted by the brain tumor diagnosis tools and then categorized as early stage or severe stage. The condition may be detected and diagnosed much more quickly by medical professionals thanks to this pre-screening than by using more conventional procedures. Ependymoma, pineal adenoma, cerebellar adenoma, pontine adenoma, craniopharyngioma, and oligodendroglioma are all included. This thesis uses a number of AI methods to analyze MRI scans for tumors and determine whether those tumors are benign or malignant based on the characteristics collected from the scans. Multiple techniques, including AIS, GA, PSO, SVM-classifiers, and a hybrid GA-SVM approach, are used. The parameters are evaluated and the methods' performance is analyzed. At last, we compare the outcomes to determine which methods performed better in terms of detection and categorization.

KEYWORDS: Brain Tumor, Abnormal Tumors, MRI Images, computer-aided diagnosis

INTRODUCTION

In this chapter, we'll look at the decision-making mechanism that analyzes MRI scans for signs of brain tumors in order to determine a patient's prognosis. Tumor detection is determined on its absolute area. Here, a divide-and-conquer strategy is used, with the MRI images of the brain tumor being grouped and subdivided into smaller sections. Districts are smaller

sections of the image that are based on shared characteristics. The picture may be divided into any number of segments that you choose. This process will continue until unique photos of the tumor can be acquired for diagnosis. In this case, the tumor's edges are detected with the use of binary operations, making it easier to locate the tumor in the brain. The primary objective of this section is to develop a



desktop software for efficient segmentation and clustering of brain tumors shown on MRI scans. Existing systems tend to be geographically specific. Line and edge data are important in machine vision systems, and they offer a few advantages. By combining information from districts and edges, the suggested system hopes to reap the benefits of both approaches while alleviating the difficulties of either via the use of binary operations.

Checking for changes in vision, hearing, mental state, physical capabilities (vigilance, strength, coordination, reflexes, etc.), and so on may help diagnose a brain tumor. The magnetic resonance imaging (MRI) scan process is crucial in tumor detection. Analysis of the tumor begins with establishing the patient's age. The next step is to determine if the tumor is intraaxial or extraaxial, such as in the sellar or Pontocerebellar region. Fat, calcifications, contrast enhancement, cystic components, and signal intensity on T1W1 series and DWI all help characterize the tissues. T1W1 pictures often show low signal intensity for tumors, but T2W2 imaging may show higher signal intensity. Brain tumors, along with leukemia and lymphoma, are the most common forms of pediatric cancer. In order to better see the variations in brain tissues, MRI sometimes requires the injection of a specific dye into a blood artery in the patient's arm. CT scan is one of the other ways used to detect the tumor. When a doctor performs a spinal tap, he or she drains the cerebrospinal fluid that bathes the brain and spinal cord. In most cases, local anesthetic is used during this surgery. To withdraw fluid from the lower spinal area, the doctor will use a large, long, thin needle. The other one is a

biopsy or an angiography. A 3D image of the tumor may be constructed from the MRI's visual "quantum" slices of the brain. Automated tumor detection methods are crucial for tumor identification and diagnosis, as previously explained. Identifying tumors manually is a time-consuming process. The early detection and diagnosis of tumors is crucial for preventing them from progressing to a malignant state. Here, binary operation based segmentation is included in the broad category of picture segmentation. There are a plethora of methods established for determining image segmentations' identities. Several techniques for doing image segmentation from MR images are proposed in the study (Deshmukh et al, 2012).

EARLIER APPROACHES (SOM, ANN)

In order to remove the tumor from the MRI scans of the brain, Sourav Paul et al. (2013) used the SOM clustering approach. The Self-Organizing Map (SOM) method is one way to group data without human intervention. The SOM is a kind of ANN with a feedforward architecture. Segmenting brain MR images relies heavily on the SOM's analytic and visual capabilities, making it a crucial tool. The learning parameters, map topology, and map size all have a role in the quality of a SOM map. The three components of a self-organizing map are competitive interactions, cooperative interactions, and changes in synaptic weight. In a competitive network, the output layer neuron decides the value of a function called the discriminate function for each input neuron. The best discriminating neuron is the one with the biggest value. The position of the topological



neighborhood will be decided by a group of cooperating neurons. Through a process called synaptic weight adaptation, a neuron's ability to differentiate an input pattern increases at the individual level.

NOISE REMOVAL USING MEDIAN FILTER

Noise in the photos is being reduced by applying filters. Channel-based pixel-based noise cancellation. Here, we compare the average of one pixel group to the average of its neighboring groups. Noise cancellation is an area a bounded process. The process of extracting a picture begins with a call to a parametric filter, and it concludes with a call to a saturation filter. In this case, an estimate of the average pixel channel is provided by the average of nearby pixels. Dots, speckles, and stains on a picture are often accepted. Therefore, noise reduction is required so that the picture is free of distracting speckles or dots. Salt-and-pepper or speckle impulses, or Gaussian noise, a continuously fluctuating parameter, may be used to represent individual dots as a model. To get rid of it, just average or median the neighboring pixels, like a 3x3 window. The concept is somewhat analogous to low pass filtering. Noise may be reduced more successfully by using a bigger window, although features and edges may be lost in the process. Another method is weighted average filtering, which instead of averaging all the pixel values in a window, prioritizes those that are closer together and gives less importance to those that are farther apart. When all of the weights are positive, the operation is known as 2D convolution or filtering. It's the same thing as a weighted average. The name "low pass filter" comes from the fact that it

allows low frequencies through while blocking out the higher ones. All weights in a weighted mask must add up to one. The time and frequency domains of 1D signals have a distinct filter frequency response, and the 1D signal may be extended to a continuous time signal. In contrast to the predominance of low-frequency components in natural pictures, noise often covers the whole audible spectrum.

Texture-based image analysis of MR image areas. It utilizes the predicted or calculated edges to inform its area of region calculations. It's an algorithm for learning with supervision. Gray matter, white matter, and cerebrospinal fluid all make up the typical brain picture. The categorization of abnormalities is often unpredictable and seldom simple. The segmentation may also be computed in a simplified form using other segmentation approaches, such as watershed based segmentation. Pixels are labeled (Bhalchandra, 2013) and queued up at the start of the flooding process. An image's highest priority is found in a queue of similarly labeled images. The process will iterate until all of the pixels have been evaluated. The primary issue with traditional noise reduction methods is that they cause the edges to blur. While adaptive and edge-preserving methods are excellent for stationary noise, they make filters' jobs much more difficult when applied to impulsive noise.

IMAGE ENHANCEMENT USING LOW PASS FILTER

Image processing entails modifying pictures so as to emphasize certain details. Certain aspects of the picture are emphasized. This approach is problem-oriented, since the processed picture is



more suited than the original image for the intended purpose. Point processing, mask processing, and pixel-by-pixel image editing are all examples of spatial domain methods. Modifying the Fourier transform of a picture is an example of a frequency domain technique, or the two approaches might be combined. Point processing is an easy-to-learn and highly effective data processing method. The mask technique may be used to sharpen images in a 2D array or a broader nearby area. Images having a dynamic range that is greater than the range of the target display device are compressed using this method. Each pixel's surrounding grayscale distribution is used as the basis for a unique transformation algorithm. In order to improve images, spatial filtering employs spatial masks and spatial filters (both linear and non-linear). Instead of blurring, median filtering aims to minimize noise. Image processing techniques including contrast stretching, noise clipping, window slicing, and histogram modeling are all part of the point operation category of image improvement. Noise reduction, median filtering, low pass, high pass, and band pass filtering, as well as zooming, are all examples of spatial operations. Filtering options in transform include linear, root, and homomorphic. Quantifying the requirement for enhancement is the greatest challenge in picture enhancement, necessitating interactive approaches to get desirable outcomes.

Magnetic Resonance Imaging There is some thought given to improving the images. Images of the cerebrum are often regarded because of the 3D perspective they provide on the brain. Color intensity and saturation may be used to distinguish between healthy and diseased tissue. MR

scans provide a black-and-white image. Scale points in contained regions of a picture may be extracted by locating their constituent pixels. The region with high black and white values is evaluated for noise cancellation. Spots' majority portrayal will once again take into account mixed values inside the box's confines. The picture will be chosen based on the values from the comparisons. Here, 127 is believed to be the grayscale value, 0 being considered to be completely black. The database has the photos in the *. bmp format.

When a patient goes in for an MRI scan, the picture may be retrieved from their own computer database. Usually, MRI scans seem like black and white photos. In a black-and-white photo, the illusion of ash shading is achieved by showing the image as a grid of dark dots on a white background. The apparent softness of the bright black in their area is determined by the sizes of the individual spots. Providing a large grid with entries that are integers between 0 and 255, with 0 corresponding to dark and 255 to white, might enough to describe an ash scale image in great detail. Patients between the ages of 25 and 55 were included in the research. The obtained pictures were saved as BMP files in the database.

BINARY OPERATIONS ON BINARIZED IMAGES DISINTEGRATION AND DILATION

In numerical morphology, the processes of disintegration and widening play essential roles as administrators. When applied to a pair of images, the primary effect of disintegration administrator is to blur the edges of the foreground pixels (often the white ones). As a result, pixelated portions in the frontal region shrink, while



"openings" inside those regions expand. If we want to break up set A by set B numerically, we need to find all the foci x for which the decoded version of B is still included in set A. Pixels in the front should all be represented by 1s, while those in the background should all be represented by 0s. As a helpful illustration, component B is a 3x3 grid of constant 1's, with the central point being selected as the cause of the set.

To keep track of the disintegration of a double-entry image using this organizing component, we should look at all of the pixels in the picture's foreground in this way. The organizing component is placed on top of the data image at each individual pixel, with the origin of the component matching the coordinates of the corresponding information pixel.

CONCLUSION

The improved picture makes it easier to see important details. The use of MR imaging in the diagnosis of brain tumors is highly regarded. Together, the black and white pictures from an MR scan will be interpreted as the binary value 0, and the white images will be interpreted as the binary value 1. Numerous photos were taken into account, and those were further divided into smaller images so that the equalized matrix could be generated. The image's borders, regions, and curved sections that will be assigned a number value may be more easily identified using a binary operation. Typically implemented as a 3x3 matrix, this organizing component conveys information on the image's morphology. Here, we assume a normalized value that is consistent with the values of binary images. The choice of the threshold factor for the first assumption achieves this. The surface areas on the

inside, the outside, and the border are all taken into account while defining the threshold. Typically, a transform function is applied to each half of the image separately. When an image's template is very robust, the histogram's peak value may drop to a valley; this point is known as the image's threshold. It is possible to discover and identify the same using a cropping technique. When the picture is enlarged, the thickness increases, and when the image is eroded, the opposite occurs. If the pixel data is in the foreground, the organizing component will locate the surrounding pixels and provide relevant insights. Selecting features from a noise-free picture is the feature extraction process. The process of choosing and using a classifier in the proper order is an ongoing one. When a pixel is fed into a support vector machine, the machine analyzes it in relation to its neighbors and returns information that may be used. Assuring they are comparable is a great benefit. The improved image is at its maximum inside the defined area. Segmentation based on the data set produced by the winner neuron will pinpoint the precise location of the tumor. Mean, median, and standard deviation of pixels will be used to do this. Thus, using this method, tumor regions were discovered in 24 of 25 database photos, all of which were previously classified as abnormal. The proposed algorithm is 97% effective in clearing normal pictures. The suggested method dealt with positive enhancements to a number of additional visual characteristics, including intensity, shape, and texture. The tumor's normal and pathological state may be predicted using the binary operations system concept. Similarly, the time limitation and relook



constraint for tumor diagnosis may be alleviated by enhancing the same in the extended binary operations approach.

REFERENCES

1. Abdulbaqi, HS, Mat, MZ, Omar, AF, Bin Mustafa, IS & Abood, LK 2014, 'Detecting brain tumor in magnetic resonance images using hidden Markov random fields and threshold techniques', Research and Development (SCORED)-IEEE conference, School of Physics., University of Sains Malaysia, Miden, Malaysia, pp. 1-5
2. Acharyya M & Malay K 2007, 'Image segmentation using wavelet packet frames and neuro fuzzy tools', International Journal of Computational Cognition, vol. 5, pp. 27-43.
3. Aissaoui, H, Gouskir, M, Elhadadi, B, Boutalline, M & Bouikhalene, B 2014, 'Automatic brain tumor detection and segmentation for MRI using covariance and geodesic distance', ICMCS Sultan Moulay Slimane University, Beni Mellal, Morocco, pp. 490-494
4. Ali, SM, LoayKadomAbood & RababSaadoonAbdoon 2014, 'Clustering and enhancement methods for extracting 3D brain tumor of MRI images', International Journal of Advanced Research in Computer Science and Software Engineering, vol. 3, no. 9, pp. 34-45.
5. Allam Zanaty, E 2013, 'An adaptive fuzzy c-means algorithm for improving MRI segmentation', Open Journal of Medical Imaging, Vol. 3 no. 4, pp. 125-135.
6. Aloui, K & Naceur, S 2009, '3D brain tumor segmentation using level

- set method and meshes simplification from volumetric MR images', World Academy of Science, Engineering and Technology, vol. 57, pp. 127-131
7. Alsutanny Y & Aqel M 2003, 'Pattern recognition using multilayer neural genetic algorithm', Neurocomputing, vol. 51, pp. 237-247.
8. Amsaveni, V, Singh, NA & Dheeba, J 2013, 'Computer aided detection of tumor in MRI brain images using cascaded correlation neural network', Fourth International Conference of Sustainable Energy and Intelligent Systems (SEISCON 2013), pp. 527-532
9. Anbeek, P, Koen, L, & Max, V 2008, 'Automated MS Lesion segmentation by K-Nearest Neighbour classification, The MIDAS online Journal', (<http://hdl.handle.net/10380/1448>). Riley, D 1992, 'Industrial relations in Australian Education', in Contemporary Australasian Industrial Relations: Proceeding of the Sixth AIRAANZ Conference, ed. Blackmur, AIRAANZ, Sydney, pp. 124-140.
10. Arjan, S, Willem, M, Edelenyi, F, Jack A & Lutgarde B 2004, 'Combination of feature reduced MR spectroscopic and MR imaging data for improved brain tumor classification', Nuclear Magnetic Resonance, vol. 18, pp. 34-43.
11. Bazin, P & Dzung P 2007, 'Topology preserving tissue classification of magnetic resonance brain images', IEEE Transactions on



Medical Imaging, vol. 26. pp. 487-496.

12. Bhattacharya, S, Manlik, U & Dutta, P 2008, 'A pruning algorithm for efficient image segmentation with neighbourhood neural networks', IAENG International Journal of Computer Science, vol. 35, no. 2, pp. 35-40