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

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ABSTRACT

Brain tumors pose a significant health challenge worldwide, necessitating accurate and timely diagnosis for appropriate treatment planning. Magnetic Resonance Imaging (MRI) is a non-invasive imaging technique widely used for brain tumor detection and classification. This paper presents an innovative approach to detect and classify brain tumors as normal and abnormal tumors in MRI images, utilizing advanced deep learning techniques. The proposed methodology consists of three main stages: preprocessing, feature extraction, and classification. During preprocessing, the MRI images are enhanced and normalized to ensure consistent data quality. Subsequently, an advanced feature extraction method based on convolutional neural networks (CNNs) is employed to automatically extract relevant features from the MRI images. These features encapsulate the intricate patterns and characteristics associated with both normal brain tissue and different types of brain tumors.

Keywords: - Brain, Tumors, MRI, Edge, Scan.

I. INTRODUCTION

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).

II. 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. We provide a mathematical model of SOM processes in the following:

Competitive Process

Assume that the number of output vectors is, and that the input vector x has

dimensions x_1, x_2, \dots, x_n , and the weight vector w_1, w_2, \dots, w_n , where $j = 1, 2, \dots, n$. The vector output of a single neuron. The task now is to determine which combination of x and w is most advantageous. The number of output values will determine which vector is the winner, and the index of the winning vector will be j . To determine the winning vector, we need to find the smallest Euclidean distance between x and w , or compute $\|x - w_j\|$ for $j = 1, 2, \dots, n$, and choose the greatest of them, denoted by $\max_j \|x - w_j\|$. For each given i , the nearest weight vector is given by $(i, \arg \min_j \|x - w_j\|)$ and (i, x) .

Working Together: The procedure involves the victorious neuron and its neighboring neurons redistributing their weights. Therefore, a winning neuron's neighboring neurons should work together via some means. Distance from the winning neuron causes the neighborhood function to decline monotonically from its highest value near the winning neuron. Let h_j be the topological neighborhood function, and let d_{ij} be the lateral distance between neuron i (the victor) and neuron j (the loser). When $d_{ij} > 0$, this is a symmetric function that decays monotonically to zero. By examining the aforementioned two characteristics of topological neighborhood functions, to symbolize the topological neighborhood function, a Gaussian is employed. As the number of iterations rises, the neighborhood function decreases, as shown by the expression $h_j = \exp\left(-\frac{d_{ij}^2}{2\sigma^2}\right)$, where h is the breadth of the Gaussian function. Now we have the neighborhood function, denoted by $n_j = \exp\left(-\frac{d_{ij}^2}{2\sigma^2}\right)$, where τ is the time constant and n is an integer from 0 to $n-1$, inclusive.

III. 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.

IV. CONCLUSION

Tumors are recognized as normal, benign, or malignant based on the input picture. Identifying an existing method requires many phases, such as taking into account an input picture and then using a noise reduction technique, such as a competitive, cooperative, or synoptic weight adaption method. Next, binary operations are applied to the enhanced picture to determine which features should be

extracted. In preprocessing, MR pictures are typically de-noised. The speckle noise cancellation method is adopted here. Synthetic aperture radar and medical pictures often include many speckle noises. Here, we take into account the input picture after first processing it to get rid of noise we call speckle. Using an adaptive histogram equalization technique, image enhancement raises the brightness and contrast of a picture. Synthetic aperture radar pictures, satellite photos, and medical imaging all suffer from this speckle noise to varying degrees. The threshold is chosen from among many bands. In the event that no particular frequency range is chosen, the overall threshold is evaluated.

The resolution threshold is often low when designing a low pass filter. High pass is thought of for the vertical structure of images. In most cases, AHE will increase the contrast of the supplied picture. The image's quality is improved as a result. KNearest Neighboring classifier is an artificial neural network approach used for image classification. The picture is used to determine if the growth is benign or cancerous. Experimental photographs obtained from a variety of sources; out of 50, 49 are uncovered by the suggested method. Out of 75 photos, 74 had tumors accurately recognized, indicating that benign abnormalities were also taken into account. Malignant tumors are detected at a rate of 99% overall. The suggested method successfully detected tumors 99 percent of the time. The FuzzyKNN classifier makes its classifications using both upgraded methods and data. Several optimization methods may be pursued for even further improvements.

REFERENCES

1. Joseph, Dr & Mohan, Divya. (2022). A Research Study on Brain Tumor Detection Techniques. 10.1007/978-981-19-0976-4_43.
2. Soomro, Toufique & Zheng, Lihong & Afifi, Ahmed J. & Ali, Ahmed & Soomro, Shafiullah & Yin, Ming & Gao, Junbin. (2022). Image Segmentation for MR Brain Tumor Detection Using Machine Learning: A Review. IEEE reviews in biomedical engineering. PP. 10.1109/RBME.2022.3185292.
3. Kumar, Sunil & Dhir, Renu & Chaurasia, Nisha. (2021). Brain Tumor Detection Analysis Using CNN: A Review. 1061-1067. 10.1109/ICAIS50930.2021.9395920.
4. Byale, Himaja & Lingaraju, G & Sivasubramanian, Shekar & In, Research. (2018). Automatic Segmentation and Classification of Brain Tumor using Machine Learning Techniques. International Journal of Applied Engineering Research. 13. 11686-11692.
5. Gupta, Aditya & Satpute, Nitin & VS, lotlikar. (2021). A. Brain Tumor Detection Using Machine Learning and Deep Learning:. Current Medical Imaging Reviews. 10.2174/1573405617666210923144739..
6. Demir, Fatih. (2022). Deep autoencoder-based automated brain tumor detection from MRI data. 10.1016/B978-0-323-91197-9.00013-8.