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Enhancing Image Registration Techniques in Medical Imaging Using Machine Learning

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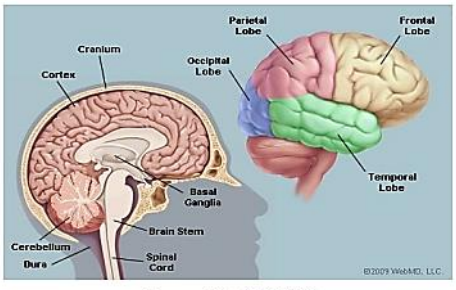
Abstract: This research demonstrates a computer-assisted approach for identifying and segmenting brain tumors, which is based on methods of image registration and classification. The method may be found here. Image registration, transformation using Contourlet, extracting features, feature normalization, feature classification, and feature segmentation are all elements that make up this suggested research. For the purpose of tumor detection and segmentation using brain MRI, we first use a Genetic Algorithm (GA) to optimize the features that have been extracted, and then we use an Adaptive Neuro Fuzzy Inference System's (ANFIS) classification method to classify the features that have been extracted. The method that has been proposed for diagnosing brain cancers is given a quantitative examination in which the method's sensitivity, specificity, segmented precision, precision, accuracy, and Dice similarity coefficient are measured. In addition, the findings of this research provide a strategy for developing a framework for the diagnosis of brain tumors by combining a number of different classification approaches. The clarity of the pictures' low-resolution boundaries may be improved by integrating brain MRI scans taken from a data collection that is freely accessible to the public..

Keywords*: Contourlet transform, and feature extraction, classifications and segmentation. Adaptive Neuro Fuzzy Inference System (ANFIS) classification*

1. Introduction

The brain is a sensitive organ that regulates human behavior and bodily functions. It regulates our perceptions, recollections, and feelings. The nervous system connects the brain to every part and organ of the body so that the brain may send instructions to the body. The spinal cord is attached to a select number of internal organs and is therefore under the direct control of the brain. There are billions of nerve cells in the brain, and these cells talk to one another through synapses. The lobes and internal structure of the human brain are shown in Figure 1.



(Source: WebMD 2009)

Fig. 1. Internal structure of brain

Meninges are a membrane-like tissue covering the skull and spinal cord, which plays a role in cognition, sensation, and movement. Cerebrospinal fluid (CSF) & soft brain tissues are also found in the brain. In addition to minerals and carbohydrates, the cerebrospinal fluid also contains white blood cells and enzymes. It is the cerebrospinal fluid that shields the brain and spinal cord from harm. This fluid travels via channels called ventricles all the way around the brain and spinal cord. Gray Matter (GM) and White Matter (WM) are the two types of soft brain tissues. There is a skeleton around the brain to protect the brain's soft tissues from harm. The GM, which is composed of neurons and regulates brain activity, is sometimes referred to as neuroglia or glia. Axons that have been removed make up the WM fibers. The cerebral aqueduct links the cerebral cortex to the rest of the brain. The skull prevents damage to the brain. The term "skull stripping" refers to the surgical removal of the skull, meninges, and scalp, all of which are non-cerebral tissue regions. The effectiveness of a tumor identification procedure is impacted by the skull stripping process. The intricacy of the brain and the wide range of MRI scanner settings provide significant obstacles to this stripping process. Brain imaging features are shown in Figure 2.

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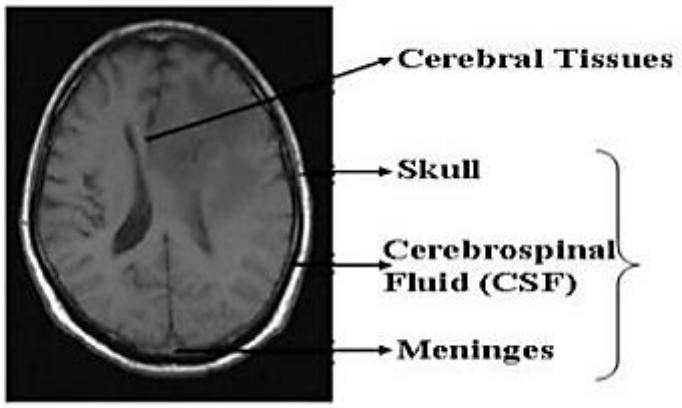

Fig. 2 Brain image details

Brain tumor MRI scans are shown in Figure 3. On the left side of this MRI, the top arrow points to the tumor, while the bottom arrow points to the white matter. Similarly, the top arrow on the MRI's right side denotes the skull, while the bottom arrow points to the brain.

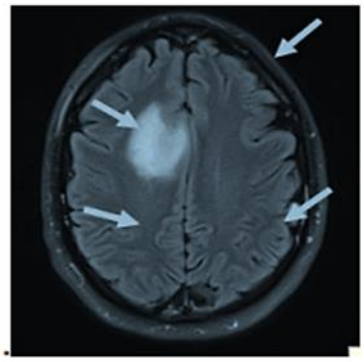

Fig. 3 MRI of brain tumor

Types of Brain Tumor

The proliferation of tumor cells in the brain cannot be stopped. The brain's blood arteries, cells, and neurons may all contribute to the tumor's growth. There are two main categories of brain tumors: primary and secondary. This kind of tumor grows slowly and seldom metastasizes to other parts of the brain. Tumors that develop quickly and spread across the brain are the later kind. Unlike malignant tumors, benign tumors do not spread to nearby organs and blood vessels. It worsens with time and eventually kills the host. Brain tumors may be broken down into the following categories:

Noncancerous brain tumors (i)

Invasive gliomas of the brain When applied to brain tumors, the words benign and malignant are very deceptive. In contrast to malignant tumors, which are thought to be cancerous, benign tumors are generally regarded to be innocuous masses of tissues in other organs. However, brain tumors, whether benign or malignant, have historically proven to be lethal. Below, we'll go over some of the clinical characteristics of these tumors.

Under the microscope, tumor cells that seem benign are considered to be benign brain tumors. These tumors develop slowly, have distinct boundaries that create a capsule, and are unable to metastasize (spread) to nearby brain structures.

Malignant brain tumors are aggressive and may spread to healthy brain tissue around them, although they metastasize very seldom. These tumors may develop slowly or rapidly, posing a significant risk of death due to their ability to penetrate healthy tissue. Malignant brain tumors are difficult to remove without damaging healthy brain tissue and have the potential to spread to other parts of the brain and spine.

There are around twenty distinct kinds of brain cells from which primary brain tumors may develop. They are classed and given names based on the specific cells that generate them. Primary brain tumors don't spread to other parts of the body very often, and when they do, it's usually inside the brain itself.

iv) High-grade tumors develop and spread quickly, whereas low-grade ones progress slowly and can lie dormant for lengthy periods of time. Surgical excision of a high-grade brain tumor often necessitates the removal

of a significant quantity of healthy brain tissue around the tumor.

Convolutional Neural Networks (CNN) are used in this study for the detection and classification of aberrant brain MRI images. In current approaches, MRI scans of the brain are analyzed using machine learning algorithms specifically designed to identify and categorize pictures of tumors. The method of classifying brain MRI scans involves a vast number of external characteristics and needs extensive pre-processing stages. This chapter provides a useful technique for detecting and classifying brain tumors using a CNN classification approach, which overcomes the drawbacks of traditional approaches. This method does not call for any intricate preprocessing actions or additional characteristics from the photos themselves. Instead, it uses this architecture to produce those internal details. Therefore, deep learning algorithm implementation results in excellent accuracy while segmenting tumors.

2. Literature Review

Hanjiang He et.al(2022) Medical picture fusion and target recognition are only two examples of the kinds of difficult activities that rely on brain medical image registration technology. The process of registering images is crucial in the field of medical imaging. Rigid image registration and non rigid image registration are two types of medical image registration that are distinguished by the types of pictures they are intended to register. In this study, we address the use of double immunofluorescence labeling technology in our research on medical image registration algorithms.

Thomas Küstner et.al (2021) A technique that is based on deep learning is presented here in order to rapidly and accurately encode the undersampled k-space data. The core concept is founded on the recently established technique of optical flow-based registering known as Local All-Pass (LAP). Using fully-sampled and highly-accelerated (with two inadequate sampling strategies) 3D inhaling motion-resolved MR images, the proposed LAPNet is evaluated on a cohort of forty patients with suspected liver or lung cancer metastases and 25 healthy subjects. The results are compared to conventional and deep learning image-based registrations. On a consistent basis, the performance of the recommended LAPNet was superior to that of image-based approaches over a broad variety of test trajectories and acceleration levels.

Jean-Marie Guyader et.al(2020) Current research suggests recasting multichannel registrations as a groupwise picture registration issue. We use this to create a technique for the registration of two or more multichannel pictures that is intrinsically transitive consistent since it is symmetric (all images play the same role during the registration operation). Our proposed technique may be used to an any set of multichannel pictures with arbitrary channel counts, and it can account for correlation between any two images regardless of channel pairing.

3. Materials and Methods

Materials

The BRATS 2015 and Brain Web public brain imaging datasets are used in this chapter. There are 129 healthy brain MRI scans and 78 abnormal brain scans in the BRATS 2015 dataset. There are 162 healthy brain MRI scans and 65 aberrant scans taken from the Brain Web dataset. Each set of brain images comes with its own set of "ground truth" pictures. We distinguish between T1-, T2-, and Proton Density (PD)-weighted images in the Brain Web dataset. Images in the BRATS dataset are 512 pixels wide by 512 pixels tall, whereas those in the Brain Internet dataset are 256 pixels wide by 256 pixels tall.

Methods

In this study, we present a fusion-based classification strategy for constructing a brain tumor detection framework. Internal low-resolution border pixels are improved by fusing brain MRI images from an open-access dataset. Now, the non-linear coefficients metric patterns are extracted from the merged brain picture using the Curvelet transform. The suggested Extreme Learner Adaboost Classification (ELAC) method is then used to categorize the features calculated from the altered non-linear coefficient metric patterns in order to distinguish between tumor-affected and unaffected brain pictures.

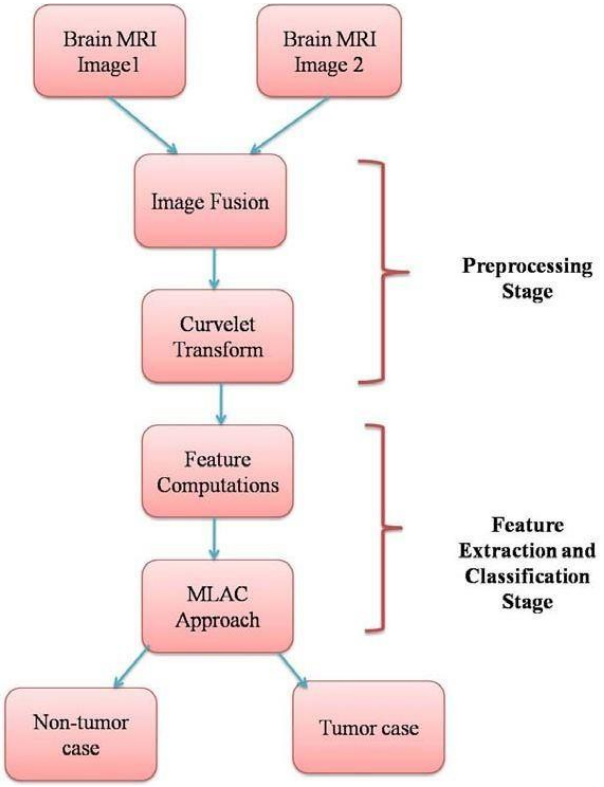

Fig. 4 shows the detailed developments of proposed brain tumor detection and classification system.

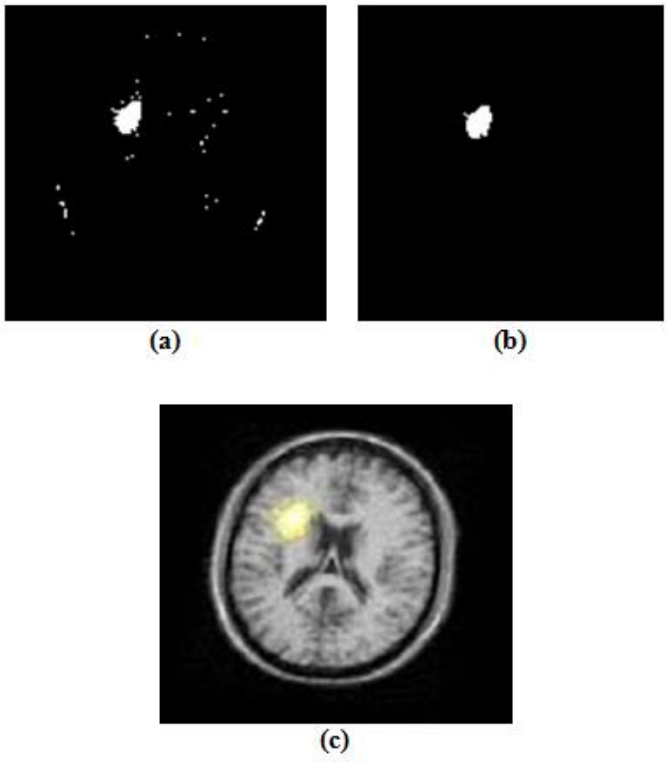

Fig. 5 (a) Dilated image (b) Eroded image and (c) Tumor regionmarked brain MRI image

Dialation is a method that repairs each damaged pixel in a categorized abnormal tumor picture of the brain (Figure 5).

The segmented tumor areas for the BRATS 2015 dataset are analyzed for their index metric parameters, which are shown in Table 1. On the BRATS 2015 dataset, the suggested ELAC method achieves a sensitivity of 98.5%, a specificity of 98.7%, and an accuracy of 99.5%. When applied to the identical picture sequences in the BRATS 2015 dataset, the ANFIS classification approach achieved a sensitivity of 96.7%, a specificity of 97.4%, and an accuracy of 97.8%.

Table 1. Index metric parameters analysis of segmented tumor regions with respect to different classification approaches on BRATS 2015 dataset

Image sequences	Proposed ELAC Approach (Chapter 4)			Image registrationbased ANFIS approach (Chapter 3)		
	Se (%)	Sp (%)	Acc (%)	Se (%)	Sp (%)	Acc (%)
Image1	98.1	98.7	99.1	95.2	97.8	98.7
Image2	98.6	98.9	99.6	96.1	98.1	98.5
Image3	98.5	98.7	99.9	97.6	98.7	99.1
Image4	98.4	98.7	99.5	94.8	96.9	99.5
Image5	98.8	98.9	99.7	93.9	98.5	97.9
Image6	98.9	98.5	99.5	98.7	98.9	98.6
Image7	98.1	98.8	99.8	96.8	96.8	98.7
Image8	98.5	98.9	99.3	95.4	94.9	98.6
Image9	98.7	98.1	99.5	96.1	98.1	99.4
Image10	98.6	98.8	99.1	97.9	98.7	98.7
Average	98.5	98.7	99.5	96.2	97.7	98.7

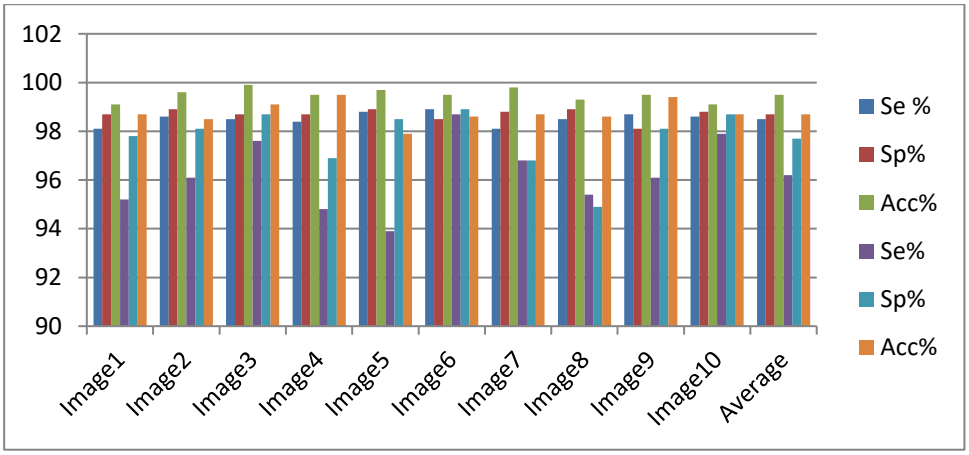

Fig 6. Graphical plot segmented tumor regions

4. Conclusion

This study recommends an effective way for identifying and separating brain tumors via the use of an image registration technique. Images are registered, transformed using a contourlet, and then features are extracted, normalized, classified using the ANFIS algorithm, and segmented using morphological operations. The suggested approach for detecting and segmenting brain tumors is tested on a collection of brain pictures from the BRATS 2015 dataset, and its performance is compared to state-of-the-art methods.

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