A Novel Content Based Image Retrieval for Human Brain Tumor Magnetic Resonance Imaging

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Abstract: With increasing amount in neuro patients which increases workload on small group of radiologists, a new system is needed that help radiologists for getting essential information like types of image, extraction of tumor and retrieve the similar images for references to take treatment planning for neuro patient. CBIR is the method by that one searches for similar pictures in keeping with the content of the similar image, like color, texture, shape, then forth. The field of representing, organizing and searching images based on their content rather than image annotations. A method framework with efficiency retrieving images from a group by similarity. The retrieval depends on extracting the acceptable characteristic quantities describing the specified contents of images. Additionally, appropriate querying, matching, categorization are needed. This approach retrieves or searches digital images from giant databases exploitation the content of the image themselves or syntactic image options without human involvement. To assist image retrieval, techniques from statistics, pattern recognition, signal process, and computerized vision are deployed commonly. Different terms used interchangeably for CBIR by image content (QBIC) and content-based visual info retrieval (CBVIR).

Keywords: Brain Tumor, MRI Image, Image Processing, Image Retrieval, CBIR, CBVIR, QBIC.

1. INTRODUCTION

The human brain may be affected by various disorders such as brain strokes, tumors, brain atrophy and genetic mutations. Surveys reveal that brain disease deaths are going up at an alarming rate. Early detection of brain diseases can significantly reduce the mortality rate. Tumors are caused by uncontrolled cell proliferation. Gliomas are the primary malignant brain tumors with two categories — Low-Grade Gliomas (LGG) and High-Grade Gliomas (HGG). In 2016 [1], the World Health Organization (WHO) updated brain tumor grading according to the increasing aggressiveness from grade I to grade IV. Grade I and II tumors are semi-malignant tumors, while grade III and IV gliomas (Glioblastoma multiforme — GBM) are malignant and certainly cause the patient's death. The anatomy and pathology information in Brain MRI are essential for disease diagnosis and therapeutic planning [1]. Many non-invasive methods are used in tumor- imaging in clinics. Magnetic Resonance Imaging (MRI) gives better soft tissue contrast than X-rays, Magnetic Resonance Spectroscopy (MRS), CT (Computed Tomography) and PET (Positron Emission Tomography) imaging modalities. T1-weighted (T1W), T1C weighted (T1CW), T2-weighted (T2W) and Fluid-Attenuated Inversion Recovery (FLAIR) are the most widely used MRI modalities. Neuropathologists and radiologists use textural and structural information from these four modalities for efficient and effective patient care. Diagnosis and treatment of brain tumor cost is very large and it lasts for a longer period. The doctors need to check on the every stage of the disease and takes last examination as referral to develop the treatment plan for the next therapy. As each year, neuro patients are increased which lead to lot of manual workload on small Radiology group. Therefore, a system is needed that provide the Radiologists an essential information like type of images, detection of tumor and similar case images from the large database and take these data as a reference for taking accurate decision for treatment planning for Neuro patients. CBIR is a process of retrieving the most similar images from the large database as per the visual content of the images and gives the essential information like type of images. CBIR

(Content-Based Image Retrieval) has become a vivid area of research in image search applications, specifically in the medical domain, over the last decade [2].

As a lot of digital pictures in medical fields become out there for clinical identification, medical education, and analysis, finding clinically relevant and visually similar pictures (or regions) according to their visual contents is greatly helpful. Content based image retrieval (CBIR), which may be applied to deal with this task, is one of the foremost active analysis areas in medical image process. There's an upscale resource of previous work on this subject, together with the retrieval of magnetic resonance imaging (MRI), CT, Dynamic positron emission Tomography, Ultrasound and Pathology images.

Content based image retrieval is utilized for giving so as to recover pictures from database inquiry. Image components can be communicated regarding shading, shape and surface. MRI is the exploration region in PC vision and image identifying to analyze and treat disease [3]. MRI is utilized as a part of radiology to investigate, capacity of the body for breaking down wellbeing and recognizing illness. MRI scanners hold solid attractive field and radio waves to shape pictures of the body. This exploration arrangement to spread the data of the Content Based Image Retrieval way to deal with the viable utilization of therapeutic picture and to separate between the typical and abnormal pictures in a particular attribute. In the medical field, applications of CBIR are often divided into two classes.

1. Retrieval of same anatomical parts: considering the same body structure in several images to identify the similarity, using preprocessing attributes like color shape, intensity and texture of the image to characterize image contents.
2. Retrieval of clinically similar lesions (e.g., lesions of the same pathological category): A solely lesion of constant pathological category area of the image is expected to be retrieved.

Thus, the text-based retrieval leads to inaccuracies during the retrieval process. Whereas CBIR retrieves similar images from the database based on shape, texture, location and grey level features of the image. This has motivated research and development in CBIR in the medical domain [4].

1.1. Magnetic Resonance Image (MRI) Process

Biomedical image processing is used frequently in detecting brain tumour from MRI images. It requires special skills and techniques because they are difficult to detect in the initial stages [1].

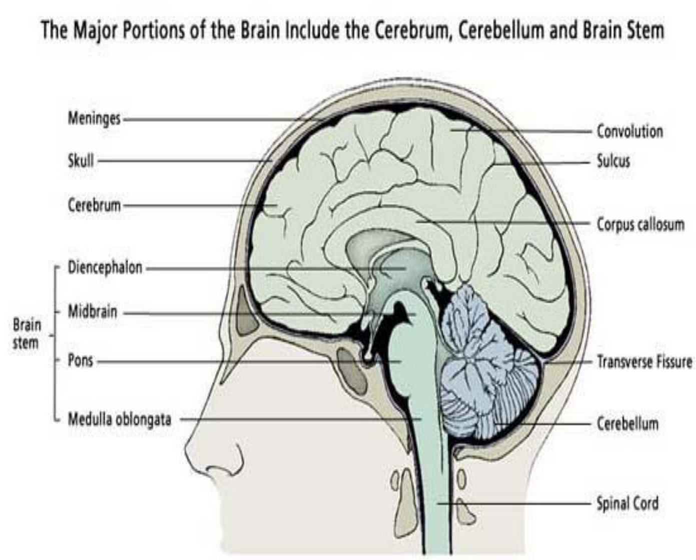

Fig. 1.1: - Structure of Human Brain

A group (mass) of abnormal *cells* that starts in the brain .There are over 120 different types of brain tumors, which makes powerful treatment muddled. Each year more than 200,000 people in the United States are diagnosed with a primary or metastatic brain tumor. Brain cancer remains difiicult to cure , with an average survival period of one to two years.

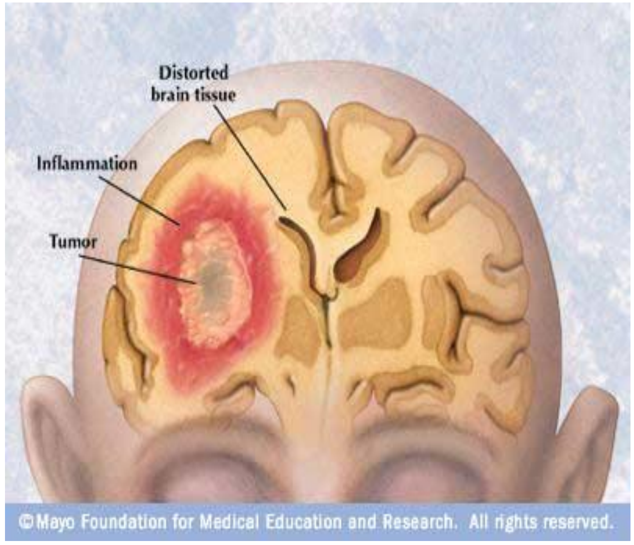

Fig. 1.2: - Tumour Affected Part

The chances of surviving for a person with a brain tumor greatly depends on all of the following:

1. Type of tumor
2. Size of the extent
3. Location of the tumor
4. Presence or absence of metastasis
5. Age
6. Overall health, and medical history

Diagnostic tools include: patient history, a brain scan, CT scan, MRI. MRI provides a much greater contrast between the different soft tissues of the body than computed tomography (CT) does. The first MR image was published in 1973.

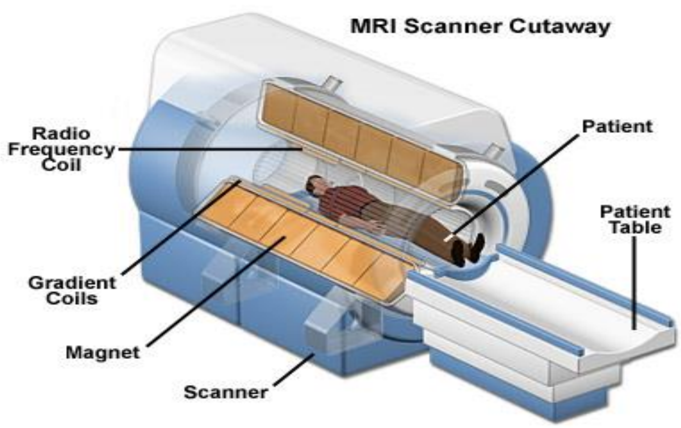

Fig. 1.3: MRI image

1. The body is largely composed of water molecules.
2. Each water molecule has two hydrogen nuclei or protons
3. Powerful magnetic field causes the magnetic moments of some of these protons to align with the direction of the field.
4. The protons in different tissues return to their equilibrium state at different rates.

The goal of the CBIR techniques is to find out the

1. Number of Tumor
2. Number of Abnormal cells
3. Tumour Margins

MRI sequences

- echo time - TE
- repetition time – TR
- T1
  - ➢ With short Te and short Tr
    - ▪ T1-weighted scans use a gradient echo (GRE) sequence,
    - ▪ This scan runs very fast allowing the
  - ➢ Easy too collect high resolution 3D datasets. T1-weighted scans provide good gray matter/white matter contrast.
- T2
  - ➢ Long Te and long Tr
  - ➢ Well suited to edema as they are sensitive to water content
- Diffusion MRI
  - ➢ Diffusion MRI calculates the diffused water molecules in the tissue of the body.
  - ➢ If molecules in a particular diffuse principally in one direction
  - ➢ The majority of the fibers in this area are going parallel to that direction.
- Fluid Attenuated Inversion Recovery (FLAIR)
  - ➢ Inversion-recovery pulse sequence used to null signal from fluids.

2. RELATED WORK

Content-based image retrieval is a very demanding application in the medical field since it can provide the physician a decision support in the diagnosis of diseases by retrieving relevant cases. The features used to retrieve general images may not apply to medical images. The knowledge of the acquired medical images and disease characteristics is necessary to extract appropriate features of the medical images.

Swati, Z. N. K., et al., (2019), addressed the key challenge in CBIR systems for MR images is the semantic gap between the low-level visual information captured by the MRI machine and the high-level information perceived by the human evaluator [5]. The traditional feature extraction methods focus only on low-level or high-level features and use some handcrafted features to reduce this gap. It is necessary to design a feature extraction framework to reduce this gap without using handcrafted features by encoding/combining low-level and high-level features. Therefore, the authors introduced a deep convolutional neural network VGG19-based novel feature extraction framework and apply closed-form metric learning to measure the similarity between the query image and database images. The authors proposed a block-wise fine-tuning strategy to enhance the retrieval performance. The extensive experiments are performed on a publicly available CE-MRI dataset that consists of three types of brain tumors (i.e., glioma, meningioma, and pituitary tumor) collected from 233 patients with a total of 3064 images across the axial, coronal, and sagittal views.

Bansal, S., & Mehan, V. (2021), focus on the key test in Content-Based Medical Image Retrieval (CBMIR) frameworks for MRI (Magnetic Resonance Imaging) pictures is the semantic hole between the low-level visual data caught by the MRI machine and the elevated level data seen by the human evaluator [6]. The Fleecy gathering is another packing technique, which is applied in plan depiction here and SVM (Support Vector Machine) is applied. The authors implemented SVM & FCM. It is essential to design a part extraction framework to diminish this opening without using painstakingly gathered features by encoding/joining low-level and critical level features.

Kobayashi, K., et al., (2021), proposed a neural network architecture to decompose the semantic components of medical images into two latent codes: normal anatomy code *and* abnormal anatomy code [7]. The normal anatomy code represents counterfactual normal anatomies that should have existed if the sample is healthy, whereas the abnormal anatomy code attributes to abnormal changes that reflect deviation from the normal baseline. By calculating the similarity based on either normal or abnormal anatomy codes or the combination of the two codes, our algorithm can retrieve images according to the selected semantic component from a dataset consisting of brain magnetic resonance images of gliomas. To evaluate whether the retrieved images are acquired according to the targeted semantic component, the overlap of the ground-truth labels is calculated as metrics of the semantic consistency.

Arai, H., et al., (2021), proposed a new framework, disease-oriented image embedding with pseudo-scanner standardization (DI-PSS) [8]. It consists of two core techniques: data harmonization to absorb differences caused by different scanning environments and an algorithm to generate low-dimensional embeddings suitable for disease classification. With DI-PSS, each brain image is pseudo-transformed into a brain image taken with a given reference scanner. Then, 3D convolutional autoencoders (3D-CAE) trained with deep metric learning generate low-dimensional embeddings that better reflect the characteristics of the disease. In this study, DI-PSS reduced the variability of distance in low-dimensional embedding between Alzheimer's disease (AD) and clinically normal (CN) patients, caused by differences in scanners and datasets, by 15.8-22.6% and 18.0-29.9%, respectively, compared to the baseline.

Sudhish, D. K., et al., (2024), addressed the Brain tumor diagnosis based on radiology images is tedious and highly subjective to intra and inter-observer variability; it adversely affects therapeutic planning [9]. Better medical treatment can be provided relating to similar past cases if relevant images are retrieved from an extensive medical image database. Content-Based Image Retrieval systems are potent image tools for dealing with such massive datasets. In a CBIR system, accurate classification and retrieval of similar pathological images can be effectively automated by utilising Convolutional Neural Network-based feature extraction methods. The authors presents a Content-Based Medical Image Retrieval pipeline on a medical domain using the CNN model for feature extraction and the clustering method used to index the feature map database. The proposed system applies a Multi-level Gain-based feature selection to reduce the dimensionality of the feature vectors obtained from the pre-trained CNN models.

3. MEDICAL CONTENT BASED IMAGE RETRIEVAL

3.1. Image Improvement

A visual picture delivered by PC preparing is to enhance the nature of a image by controlling picture with programming. It is entirely simple, to make a picture lighter or darker to increment or decline the contrast. Filter methods are available for image enhancement to modify images in different techniques. Programs particular for expanding improvement is once in a while called image editor [10].

3.2. Image Segmentation

The division of a images into significant structures, picture segmentation, is frequently a fundamental stride in picture examination, object representation, perception, and numerous other picture handling errands.

An incredible assortment of division strategies has been proposed in the previous decades, and some classification is important to show the strategies legitimately here [11]. A proper classification does not appear to be good however, in light of the fact that even two altogether different division methodologies might share properties that oppose particular arrangement.

The accompanying classifications are utilized:

1. Threshold based Segmentation.

Histogram thresholding and cutting procedures are utilized to portion the picture. They might be connected straightforwardly to a picture, yet can likewise joined with pre-and post-handling procedures.

2. Edge based Segmentation.

With this strategy, recognized edges in a picture are accepted to speak to protest limits, and used to distinguish these articles.

3. Region based Segmentation.

Where an edge based strategy might endeavor to discover the item limits and afterward find the article itself by filling them in, a locale based strategy takes the inverse methodology, by (ex.) beginning amidst an article and afterward "developing" outward until it meets the item limits.

4. THE SCHEME OF TYPICAL MRI IN CBIR SYSTEM

The major substance based picture recovery which depicted in two sections: highlight extraction and grouping.

4.1. Feature Extraction

It is utilized to innate elements in pictures, for example, shape, color and composition. It serves to determination and decides the exact division of cerebrum tumor MRI pictures is vital for a right finding by these devices. Highlight extraction comprise of three levels are pixel, nearby and worldwide. The least complex visual picture components depend on pixel. Pictures are measured to normal size and analyzed utilizing Euclidean separation. Neighborhood components are extricated from sub pictures from unique pictures. Worldwide components are extricated to portray entire picture in a normal manner [12].

4.2. Classification

The primary thought of Support Vector Machine is to indicate ideal hyper plane by minimize an upper bound of the general articulation mistake through augment the separation between the isolating hyper plane and the data. It is found that expand the edge in the middle of itself and the nearest neighborhood training points [13].

The yield result from Principal Component Analysis goes to the classifier as a data. SVM characterizes the X-ray database into two classes comprising of typical pictures, and unusual pictures.

The outcomes for the proposed classifiers are analyzed in Table 1, which demonstrates the rate of order between the two distinctive picture classes.

Table 4.1: Order rate in the middle of normal and abnormal classes.

96%	No of normal images which classify as typical pictures
100%	No of abnormal images which classify as unusual lclasses

1. Image Database

The systems have been actualized on a human brain tumor MRI. All the info dataset (complete pictures is 90: 42 pictures are ordinary, 48 pictures are unusual) utilized for characterization comprises of axial, T2-weighted, 256 - 256 pixel MRI cerebrum pictures. Figure 4.1 demonstrates some specimen for separate in the middle of ordinary and unusual pictures in brain tumor MRI images.

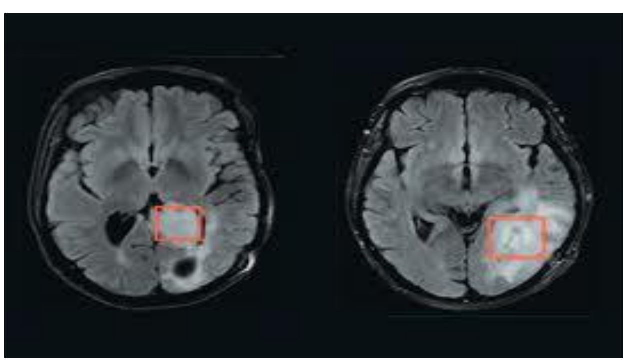

Fig. 4.1: Sample MRI images

5. BRAIN TUMOR IMAGES FOR MRI APPLICATIONS

Image registration is the procedure of taking two or more pictures of the same scene at various times, from various perspectives. It is an essential stride in all picture investigation errands in which the last data is picked up from the mix of different information sources, as in picture combination, change identification, and multi channel picture rebuilding [14].

5.1. ASSERT

Programmed Search and Selection Engine with Retrieval Instruments was produced by Purdue University, Indiana University in USA [15]. This framework removes 255 components of composition, edge, shape and dark scale properties in pathology-bearing districts.

5.2. 3D PET/CT

It underpins the powerful elucidation with entire body FDG oncology contemplates and associates with PET and CT [16]. It decides radiologists to precisely and noticeably mix PET and CT to join anatomical and utilitarian pictures. 3D permits you to independently the progressed perception and investigation instruments you require on a schedule premise.

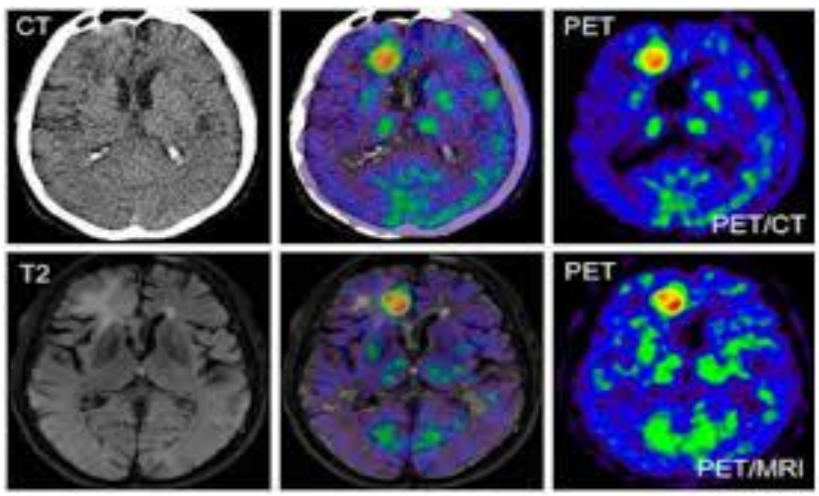

Fig. 4.2: Sample 3D PET/CT scan images

5.3. MIRAGE

It is an internet learning framework on restorative informatics. Which is arranged at Middlesex University in the United Kingdom, which covers more than 100,000 2D and 3D pictures also, encourages, for example, area, chart book and substance based recovery for both 2D and 3D pictures.

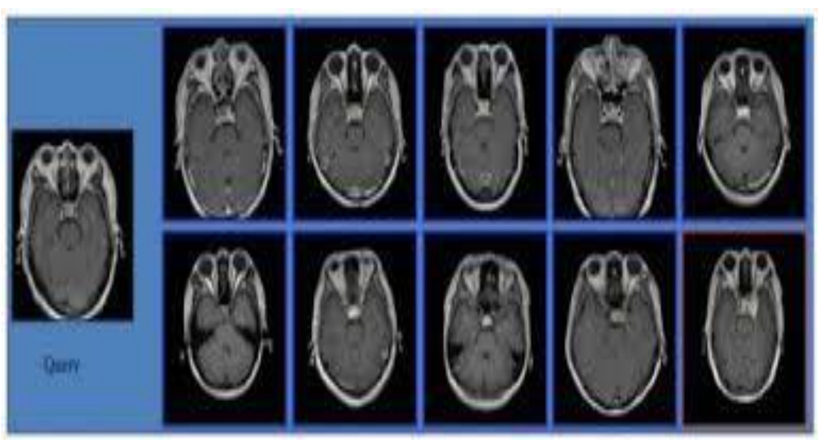

Fig. 4.3: Mirage Images

6. CONCLUSION

For the last two or three decades, the massive increase in the availability of brain MR images has created challenges in mining similar MR images from huge datasets. This scenario explains the showcase of CBIR as a vivid area of research. This paper has concentrated on CBIR Brain tumor Magnetic Resonance Imaging theories for future exploration. The general efficiency of Magnetic Resonance Imaging brain tumor picture recovery can be enhanced by the utilization of feature extraction and utilizing CBIR, investigation of quality and advancement in the therapeutic field and order. Content Based Image Retrieval and recovery of analysis brain tumor sickness has accomplished a level of development, at an examination level, at once of huge need. Subsequent to, the field has yet to make impressive assaults into standard clinical practice, therapeutic examination.

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