BRAIN TUMOUR DETECTION AND SEGMENTATION USING MACHINE LEARNING

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ABSTRACT:

Automatic segmentation of MR images of normal brains by statistical classification, using an atlas before initialization and also for geometric constraints. A most recent extension detects brain lesions as outliers and is successfully applied for the detection of multiple sclerosis lesions. Brain tumors, however, can't be modeled as intensity outliers due to overlapping intensities with normal tissue and significant size. Brain tumors are one of the most serious and life-threatening medical conditions that can affect individuals of all ages. Early detection and diagnosis are crucial for the management or treatment of brain tumors. Machine learning techniques, such as Support Vector Machines (SVM), have been applied in the medical field to aid in detecting brain tumors. In this approach, SVM is used along with data structures to analyze patient data and make predictions about the presence of brain tumors. Overall, the SVM and data structure approach can provide an effective tool for the detection and segmentation of brain tumors, potentially improving patient outcomes and quality of life.

***Keywords*__** MRI, Support Vector Machine, Data Structure, Tumour Detection, and Segmentation.

I.INTRODUCTION:

Combining image segmentation based on statistical classification with a geometric prior has increased significantly robustness and reproducibility. Using a probabilistic geometric model of sought structures and image registration serves both the initialization of probability density functions and the definition of spatial constraints. A strong prior, however, prevents the segmentation of shapes that are not part of the model. In practical applications, we encounter either the presentation of new objects that cannot be modeled with a spatial prior or regional intensity changes of existing structures not explained by the model. Our driving application is the segment of brain tissue and tumors from three-dimensional magnetic resonance imaging (MRI). Our goal is a high-quality segmentation of healthy tissue and a precise delineation of tumor boundaries.

Magnetic resonance imaging (MRI) is a powerful non-invasive image technique for studying soft tissues' anatomy and properties.The overall better quality of obtained datasets characterizes the MRI. Such data usually contains a collection of two-dimensional (2-D) MR images or a full three-dimensional (3-D) isotropic volume. It performs efficient Qualitative or user-driven quantitative analysis on MR data, but current needs are non-supervised, not automated, quantitative analysis tools. In this project, we have considered intensity nonuniform correction as a global problem involving multiple communities with different objectives.

II.LITERATURE SURVEY:

This paper presents a method for the precise, accurate, and efficient quantification of brain tumors (glioblastomas) via MRI that can be used routinely in the clinic. Tumor volume is formed for segmenting disease progression and response to the therapy and accessing the need for changes in treatment plans. We use multiple MRI protocols containing FLAIR, T1, and T1 with Gd enhancement to gather information about different aspects of the tumor and its vicinity. These include enhancing tissue, no enhancing tumor, edema, and combinations of edema and tumor. We have adopted the fuzzy connectedness framework for tumor segmentation in this stage or the method requires only limited user interaction in routine clinical use.

A novel approach to correcting for intensity nonuniformity in magnetic resonance (MR) data is defined that achieves high performance without requiring a model of the tissue classes present. The method has the advantage that it can be applied at an early stage in an automated data analysis before a tissue model is available. This intensity non uniformly usually attributed to poor radio frequency (RF) coil uniformity, gradient-driven eddy currents, and patient anatomy on inside and outside the field of view. Although these 10%–20% intensity variations have little impact on visual diagnosis, the performance of automatic segmentation techniques that assume homogeneity of intensity within each class can be significantly degraded.

Finally, the presented methods discussed the availability and usability of Magnetic resonance imaging (MRI) powerful noninvasive imaging technique for studying soft tissue anatomy and properties. It characterizes by the overall better quality of obtained datasets. Such data usually contains a collection of two-dimensional (2-D) MR images or a completed three-dimensional (3-D) isotropic volume.

III.EXISTING SYSTEM:

The motivation behind the study is to detect brain tumors and provide better treatment for the suffering. The abnormal growths of cells in the brain are called tumors and cancers are a term used to represent malignant tumors. Usually, CT or MRI scans are used for the detection of cancer regions in the brain. Positron Emission Tomography, Cerebral Arteriogram, Lumbar Puncture, and Molecular testing are also used for brain tumor detection. In this study, MRI scan images are taken to analyze the disease condition. Objectives of this research work are i) identify the abnormal image and ii) segment tumor region. The density of the tumor can be estimated from the segmented mask and it will help in therapy. A deep learning technique is employed to detect abnormality from MRI images. Multi-level thresholding is applied to segment the tumor region. Several malignant pixels give the density of the affected region.

It only focuses on using MRI scans for the detection of brain tumors. While MRI is a powerful imaging technique, it may not always be the most effective or cost-efficient option for all patients. Additionally, there is a risk of false positives or false negatives when using any imaging technique, including MRI.

Another potential limitation of the study is the use of deep learning techniques for the detection of abnormal images. While deep learning algorithms have shown promising results in medical image analysis, they require large amounts of training data and can be computationally expensive. This can limit the scalability and applicability of the approach in real-world clinical settings.

The study only utilizes multi-level thresholding for segmenting the tumor region. While this is a common approach, it may not always provide the most accurate or robust segmentation results. Other segmentation methods, such as deep learning-based approaches or region-growing methods may also be worth considering.

IV.PROPOSED SYSTEM

In our proposed system (Figure 1.1) for brain tumor detection, we will be using Support Vector Machines (SVM) and data structures to analyze patient data and make predictions about the presence of brain tumors. The system will involve collecting patient data such as age, gender, and medical history, and imaging data such as MRI or CT scans. Cleaning, normalization, and feature extraction will prepare the collected data. Data cleaning will ensure that the data is error-free and consistent, while normalization will make sure that the data is on a similar scale. Feature extraction will involve selecting the relevant features that are useful in detecting brain tumors. The proposed system will have the potential to improve the detection and diagnosis of brain tumors, leading to better patient outcomes and quality of life. It will provide an effective tool for medical professionals to accurately identify the presence of brain tumors in patients and develop appropriate treatment plans. Overall, the SVM and data structure approach can significantly benefit the medical field and the treatment of patients with brain tumors.

SVMs are a well-established machine learning algorithm that provides a reliable and accurate method for analyzing patient data and making predictions about the presence of brain tumors. By collecting patient data such as age, gender, medical history, and imaging data, the proposed system can detect brain tumors more accurately and efficiently, leading to better patient outcomes and quality of life.Data cleaning, normalization, and feature extraction ensure that the data is error-free, consistent, and on a similar scale, making it easier to compare and analyze. This approach enables medical professionals to develop appropriate treatment plans more quickly and accurately, leading to better patient care.

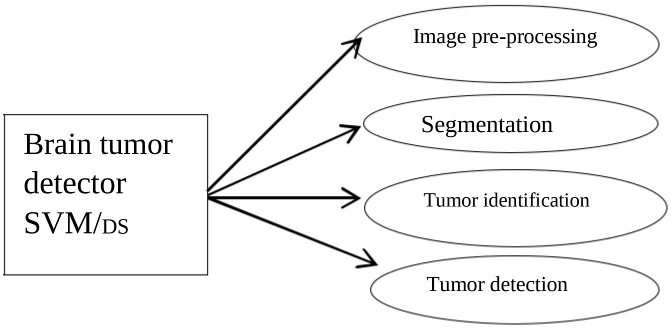


Figure 1.1 Block diagram of Brain tumor detection

A.MRI PREPROCESSING

Preprocessing images commonly involves removing low frequency, and background noise, normalizing the intensity of individual practical images, removing reflections, and the masking portion of images. Image processing is the technique of enhancing data images before computational processing (Figure 1.2). The following pre-processing steps involve realignment and unwrapping slices within a volume, separately for every modality.

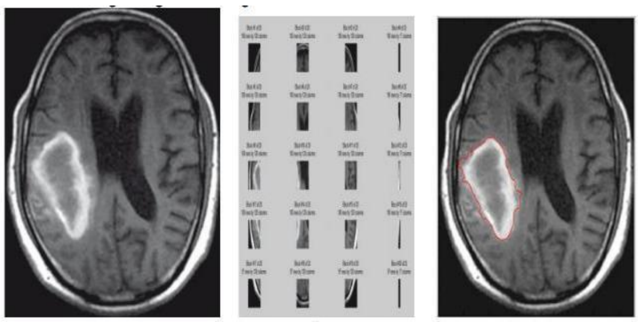


Figure 1.2: a) original MRI (b) subblocks of MRI (c) segmented tumor using CRF

B. FEATURE EXTRACTION

Feature extraction is a special form of Dimensionality reduction. When the input data to an Algorithm is too large to be processed and it is suspected to be notoriously redundant (e.g. the same measurement in both feet and meters) then the input data will be transformed into a reduced representation set of features (also named features vector). Transforming the input data into a set of features is called feature extraction. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data to perform the desired task using this reduced representation instead of the full-size input.

C.BRAIN TUMOR SEGMENTATION AND CLASSIFICATION FROM NON-TUMOR TISSUE

A support vector machine searches an optimal separating hyper-plane between members and non-members of a given class in a high-dimension feature space. The inputs to the SVM and DS algorithm are the feature subset selected during the data pre-processing step and extraction step. In SVM and DS, kernel functions are used such as graph kernel, polynomial kernel, RBF kernel, etc. Among these kernel functions, a Radial Basis Function (RBF) proves to be useful, due to the fact the vectors are nonlinearly mapped to a very high-dimension feature space. For tumor/non-tumor tissue segmentation and classification, MRI pixels are considered samples. These samples are represented by a set of feature values extracted from different MRI modalities. Features from all modalities are fused for tumor segmentation and classification. A modified supervised SVM and DS ensemble of the classifier is trained to differentiate the tumor from the non-tumor tissues.

D.SVM and DS ALGORITHM FOR SEGMENTATION IS AS FOLLOWS

Obtain the sub-image blocks, starting from the top left corner. Decompose sub-image blocks using two-level 2-D SVM and DS. Derive Spatial Gray Level Dependence Matrices (SGLDM) or Gray Level Co-occurrence matrices. For each 2-level high-frequency sub-bands of decomposed sub-image blocks with 1 for distance and 0, 45, 90, and 135 degrees for θ and averaged. From these co-occurrence matrices, the following nine Haralick second-order statistical texture features called wavelet Co-occurrence Texture features (WCT) are extracted.

D.BRAIN TUMOR SEGMENTATION USING STRUCTURE PREDICTION

In this section, the method proposed for segmentation of particular structures of the brain tumor, i.e. whole tumor, tumor core, and active tumor, is evaluated. This method is based on an approach, whose novelty lies in the principled combination of the deep approach together with the local structure prediction in medical image segmentation tasks. The modified architecture is shown in Figure 1.3.

V..MODIFIED MODEL ARCHITECTURE

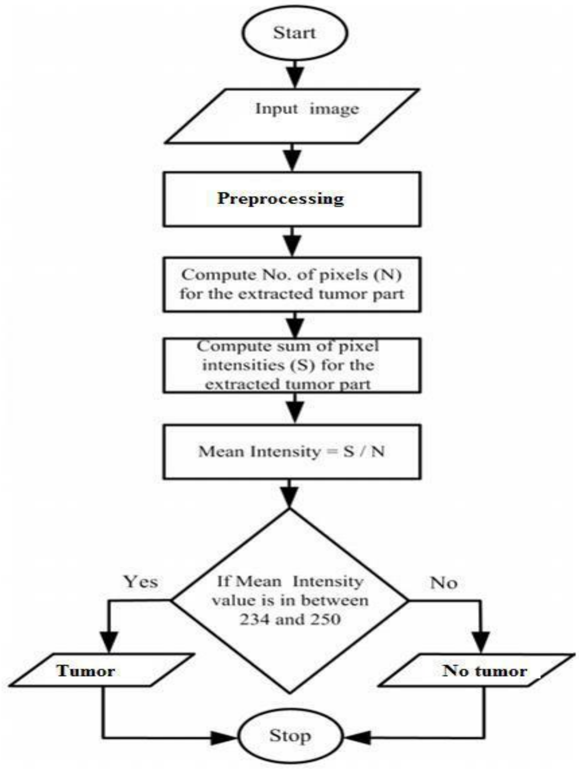
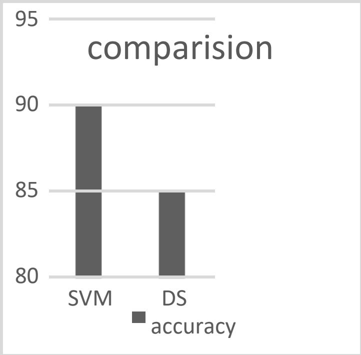


Figure 1.3 Architecture of Brain tumor segmentation process

VI. RESULT AND ANALYSIS

The proposed system for brain tumor detection using SVM and data structures has the potential to significantly improve patient outcomes by accurately identifying the presence of brain tumors.



Methods	Accuracy
SVM	90
DS	**85**

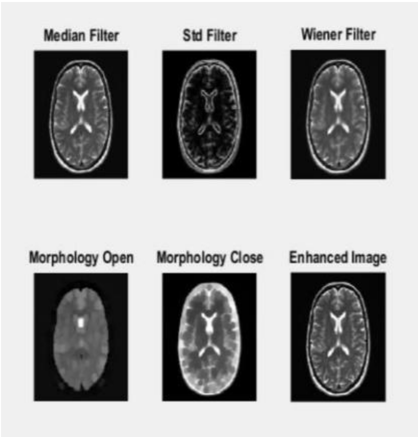


Figure 1.4:Detection using various filters

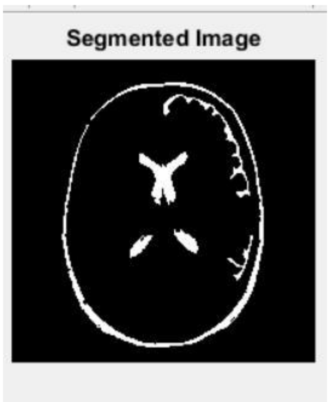


Figure 1.5: Detection and segmentation of Brain tumor

The effectiveness of the system can be evaluated by analyzing the results of its performance on test data. Once the performance of the system has been analyzed, any necessary improvements can be made to increase its accuracy and effectiveness. For example, additional features may need to be included in the feature extraction process or the SVM algorithm may need to be optimized to improve performance. Finally analysing the results of the proposed system for brain tumor detection using SVM and data structures is an important step in evaluating its effectiveness and identifying areas for improvement. By continuously analyzing and improving the system, it has the potential to significantly benefit the medical field and improve patient outcomes. SVM has given better accuracy.

VII.CONCLUSION

The proposed system for brain tumor detection using Support Vector Machines (SVM) and data structures offers significant advantages to the medical field. By collecting and analyzing patient data with reliable machine-learning algorithms, medical professionals can detect brain tumors more accurately and efficiently, leading to better patient outcomes and quality of life. The system's ability to clean, normalizes, and extract relevant features from patient data ensures that the data is error-free, consistent, and easy to compare and analyze. Ultimately, the proposed system has the potential to improve the detection and diagnosis of brain tumors, making it a valuable tool for medical professionals seeking to provide better care to patients.

FUTURE SCOPE

Furthermore, the proposed system can be extended to include other types of medical data such as clinical data or electronic health records. This would provide a more comprehensive view of the patient's health and potentially improve the accuracy of the system.

In addition to technical improvements, future work could also focus on the integration of the proposed system into clinical workflows. This would involve developing a user-friendly interface for medical professionals to access and interpret the results of the system

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