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COMPARISON OF TEXTURE ANALYSIS TECHNIQUES FOR SEGMENTATION OF BRAIN TUMORS FROM MRI IMAGES

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ABSTRACT:
Brain tumor segmentation in magnetic resonance imaging (MRI) plays a pivotal role in early diagnosis and treatment planning. Various segmentation techniques have been proposed, with texture analysis emerging as a promising method for extracting meaningful features from MRI images. This research paper presents a comprehensive comparison of existing brain tumor segmentation techniques that utilize texture analysis. The study covers a range of state-of-the-art methods, including statistical, model-based, and deep learning approaches, evaluating their performance in terms of accuracy, sensitivity, specificity, and computational efficiency. We explore the impact of different texture features, such as gray-level co-occurrence matrix (GLCM), Gray-level run-length matrix (GLRLM), and local binary pattern (LBP), on segmentation results. Additionally, the research investigates the robustness of these techniques across diverse MRI datasets and tumor types, considering factors such as image resolution, noise, and tumor heterogeneity. The experimental evaluations are conducted on benchmark datasets, and the results are analysed comprehensively to provide insights into the strengths and limitations of each approach. This research aims to guide researchers and practitioners in selecting appropriate texture-based segmentation methods based on specific clinical requirements and imaging conditions.

Keywords: Brain Tumor Segmentation, MRI Images, Texture Analysis, GLCM, GLRLM, LBP, Image Processing, Medical Image Analysis, Deep Learning, Computational Efficiency.

1. INTRODUCTION

Medical image analysis relies heavily on brain tumor segmentation, which is necessary for locating tumor-affected regions in the brain. This step is critical for precise location, treatment course, and observing disease progression. Due to its high resolution and soft tissue contrast, magnetic resonance imaging (MRI) stands out as the preferred non-invasive method for detecting brain tumors. In any case, conventional segmentation techniques depending on manual techniques are restricted by their incompatibility to image intensity variations, requiring extensive manual efforts and bringing about low accuracy.

The segmentation techniques can be comprehensively ordered into manual, semi-automatic, and fully automatic techniques. Expert manual segmentation is accurate but time-consuming, preventing scalability. Semi-automatic strategies require negligible client mediation yet include tedious associations. Machine learning (ML) and deep learning (DL) are fully automatic methods that aim to improve efficiency, consistency, and scalability. However, they have the tendency to necessitate large annotated datasets and present computational difficulties.
Utilizing their capacity to automatically learn hierarchical representations from data, convolutional neural networks (CNNs) have demonstrated superior performance in medical image segmentation tasks in recent years. In spite of this, the understanding of carefully assembled features and CNNs in brain tumor segmentation remains underexplored in the literature. Our review tends to this shortcoming by proposing an original hybrid approach that joins handcrafted features with CNNs, meaning to upgrade the general display of brain tumor segmentation in MRI scans.

To achieve high accuracy and robustness, our hybrid model combines CNNs with a variety of handcrafted features, such as intensity, texture, and shape-based features. The proposed method outperforms both individual CNN-based approaches and conventional handcrafted feature-based methods in terms of its ability to generalize to data that has not been seen. Performance is estimated against cutting edge segmentation models utilizing standard benchmark datasets, with results showing high proficiency in view of measurements, for example, segmentation accuracy, Dice score, specificity, and sensitivity. Our research has implications for real-world clinical applications, where precise and effective segmentation of brain tumors is crucial.

2. LITERATURE REVIEW

Brain tumor segmentation in magnetic resonance imaging (MRI) is the foremost requirement in clinical image examination, with applications in diagnosis, therapy planning, and disease progression. Different procedures have been utilized to accomplish precise and solid segmentation, with a specific spotlight on texture examination techniques. This paper aims to give an outline of existing investigations that consider brain tumor segmentation procedures in MRI images utilizing texture examination, featuring the qualities, restrictions, and patterns in this field.

2.1 Segmentation of Brain Tumors Using Texture Analysis:

Texture analysis assumes an important part in portraying the spatial distribution of textures in clinical pictures, giving important data about tissue heterogeneity. Techniques for texture analysis can help distinguish between healthy and pathological tissues in the context of segmenting brain tumors. These techniques shed light on the intricate patterns that exist within tumor regions.

2.2 Conventional High-quality Feature-Based Approaches:
Early ways to deal with brain tumor segmentation frequently depended on carefully assembled texture features extricated from X-ray pictures. Most of the time, intensity-based features like mean, median, and standard deviation were used, as well as texture-based features like the gray-level co-occurrence matrix (GLCM) and local binary patterns (LBP). Focusing on these routine techniques featured their restrictions in dealing with variations in image intensities and the requirement for comprehensive manual examination, prompting a loss in segmentation and accuracy.

2.3 Progressions in AI Based Strategies:
AI (ML) methods, especially support vector machines (SVM), Random Forest (RF), and k-nearest neighbours (k-NN), have been utilized related to texture examination for brain tumor segmentation. These strategies expected to further develop effectiveness and versatility via automation of the component choice interaction. While these ML-based approaches show upgraded performance contrasted with customary techniques, they actually confronted difficulties connected with versatility.

2.4 The Rise of Deep Learning and Convolutional Neural Networks (CNNs):
The appearance of deep learning, especially convolutional neural networks (CNNs), improved clinical image segmentation, including brain tumor localization. CNNs consequently gain progressive representations from data, catching complex examples and designs. Comparing CNN-based segmentation methods for brain tumors, such as U-Net, V-Net, and DeepMedic, has been the focus of numerous studies. CNNs exhibited prevalent implementation by utilizing location specific highlights, conquering issues connected with intensity varieties, and adjusting to different imaging conditions.

2.5 Difficulties and Important Entry Points in Mixture Approaches:
Patterns in brain tumor segmentation research include the investigation of semi and semi-automatic methodologies that consolidate handcrafted features with CNNs. These methodologies plan to saddle the interpretability and area information on handcrafted features while profiting from the inherent learning abilities of CNNs. Hybrid models have the potential to improve robustness, precision, and generalization, as evidenced by recent studies' promising outcomes.

2.6 Metrics and Benchmark Datasets for Evaluation:
Similar examinations in tumor segmentation utilize different assessment measurements, including segmentation accuracy, Dice score, specificity, and sensitivity. Benchmark datasets, like the BraTS challenge datasets, are usually used to evaluate the performance of various division procedures. These datasets empower normalized assessments and work with reasonable investigations across assorted techniques.

3. METHODOLOGY

In the realm of medical image analysis, handcrafted feature-based methods have been extensively employed for tasks such as brain tumor segmentation. These techniques leverage machine learning (ML) algorithms to segment images, relying on engineered features that characterize various image qualities. Handcrafted features are categorized into three types: intensity-based, texture-based, and shape-based. Intensity-based features capture local intensity distribution, providing insights into abnormal tissue regions. Texture-based features describe spatial arrangements of intensities, offering valuable information on the complexity of tumor regions. Shape-based features elucidate geometric properties, aiding in differentiation based on size, shape, and boundary characteristics. ML algorithms like random forests (RF), support vector machines (SVM), and k-nearest neighbors (k-NN) are trained post-feature extraction. However, the manual tuning required for these methods limits their precision and adaptability to diverse imaging conditions.

On the other hand, convolutional neural network (CNN)-based methods have transformed image recognition and segmentation by automatically learning features from data, eliminating the need for manual engineering. Comprising layers like convolutional, pooling, and fully connected layers, CNNs learn hierarchical representations, enhancing performance in image analysis tasks. Architectures like U-Net, V-Net, and DeepMedic have demonstrated success in brain tumor segmentation, with U-Net's symmetric encoder-decoder architecture and skip connections enabling accurate boundary localization. While CNNs excel in capturing complex patterns, they demand large, annotated datasets for training and can be computationally expensive.

To address these challenges, hybrid approaches have emerged, aiming to combine handcrafted features and DL techniques for enhanced medical image segmentation. Strategies include integrating handcrafted features at different levels of the CNN architecture, such as input channels, feature maps, or decision levels. Concatenating handcrafted features with deep features or injecting them into intermediate layers allows the model to leverage both types, encouraging complementary learning and robust feature representations. Hybrid models have shown improved performance compared to individual methods in various medical imaging tasks, showcasing the potential of synergizing domain knowledge and automated feature learning.

Various strategies, such as translation, noise addition, rotation, and shearing, have been employed to augment MRI datasets, thereby improving the performance of tumor segmentation. Khan et al. demonstrated the efficacy of noise addition and shearing in expanding the dataset size, resulting in enhanced accuracy for classification and tumor segmentation tasks. Similarly, Dufumier et al. utilized rotation, random cropping, noise addition, translation, and blurring to augment their dataset, leading to improved performance in age and type classification predictions. Elastic deformation, rotation, and scaling were identified in different studies as effective techniques to simultaneously enhance tumor segmentation and accuracy. The simplicity and effectiveness of these techniques contribute to their common use across various studies.

Beyond traditional augmentation methods, researchers have explored the generation of synthetic images to fulfil specific tasks. Notably, the hybrid method has gained popularity, involving the combination of patches from two randomly selected images to generate new synthetic images. While the literature showcases the application of diverse datasets, each with varying image quantities, researchers have also employed different network architectures in their studies. Consequently, the results obtained are dependent upon the specific techniques chosen by individual researchers.

3.1 Preprocessing

The preprocessing stage is fundamental in preparing MR images for subsequent human or machine vision system processing. Its objectives include enhancing the visual quality of MR images, improving the signal-to-noise ratio, eliminating irrelevant noise and undesired background components, smoothing the inner regions, and preserving edges. A key method employed for signal-to-noise ratio enhancement involves adaptive contrast enhancement using a modified sigmoid function.

Skull stripping is a critical step in biomedical image analysis, particularly for examining brain tumors in MR images. This process involves removing non-brain tissues, such as fat, skin, and skull, to facilitate effective analysis. Various techniques exist for skull stripping, including automatic methods using image contours, segmentation and morphological operations, and those based on histogram analysis or a threshold value. This study adopts a threshold-based skull stripping technique, eliminating extraneous tissues through a threshold operation.

Segmentation and morphological operations are pivotal for identifying infected brain MR regions. In the segmentation process, the pre-processed brain MR image undergoes thresholding, with pixel values exceeding the chosen threshold mapped to white and others to black. This results in the creation of distinct regions around infected tumor tissues. Subsequently, an erosion operation is applied to eliminate white pixels. The eroded region and the original image are then divided into two equal parts, with the black pixel region from the erosion operation serving as a brain MR image mask. Berkeley wavelet transformation is employed for effective segmentation, wherein wavelets are utilized as functions defined over finite time intervals with an average value of zero. This transformation allows the study of different frequency components separately, contributing to precise segmentation of brain MR images.

$$\Psi_{s,\tau} = \frac{1}{\sqrt{s}}\Psi\left(\frac{t-\tau}{s}\right)$$

The Berkeley wavelet transform (BWT), as explained in the literature is described as a two-layered triadic wavelet transform relevant to flag or picture handling. Like other wavelet changes, for example, the mother wavelet change, the BWT calculation works with the transformation of information from a spatial structure into the transitory space recurrence. The BWT stands apart for its viability in addressing picture changes, offering a total and orthonormal portrayal. This indicates that the transform keeps the original data's orthogonality and completeness, making it a reliable tool for signal and image processing applications. The usage of triadic wavelets in the BWT improves its capacity to catch complex specimens and designs inside images, adding to a far reaching and productive depiction in the transient space.

$$\beta_{\theta}^{\varphi}(\tau, s) = \frac{1}{s^2}\beta_{x}^{\varphi}\left(3^s(x-i), 3^s(y-j)\right)$$

The essence of morphological operations lies in rearranging the relative order of pixel values, focusing on their spatial arrangement rather than their mathematical values. As such, these operations are particularly well-suited for processing binary images. The fundamental morphological operations are dilation and erosion. Dilation operations are designed to expand the pixel boundaries of an object, effectively adding pixels to the object's boundary region. Conversely, erosion operations aim to reduce the pixels from the boundary region of objects, refining the object's shape. The decision to add or remove pixels is contingent upon the structuring element defined by the selected image, allowing for precise adjustments to the boundary regions based on the structural characteristics of the image.

Feature Extraction

Texture analysis, a step vital to image understanding, includes extricating more higher-level data from images, incorporating limitations like shape, surface, variety, and difference. This examination fills in as a significant component in both human visual discernment and AI frameworks. A fundamental work by Haralick et al. presented the Gray Level Cooccurrence Matrix (GLCM) and surface elements as broadly involved devices in image examination applications. This strategy includes a two-step process for feature extraction from clinical pictures. At first, the GLCM is processed followed by the determination of texture features extracted from GLC. Given the unpredictable designs of different brain tissues like white matter (WM), grey matter (GM), and cerebrospinal liquid (CSF) in brain MRI images, the extraction of applicable features becomes pivotal. Textural discoveries and examination assume an important part in further developing finding, tumor development at various stages, and evaluating treatment responses. A few fundamental accurate features, including Mean (M), are processed by adding all pixel values in a picture and dividing by the complete number of pixels.

$$M = \left(\frac{1}{m \times n}\right) \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} f(x, y)$$

Standard Deviation (SD). The standard deviation is the second focal acting as a measure of inhomogeneity. A higher cost shows better differentiation of edges of a image.

$$SD(\sigma) = \sqrt{\left(\frac{1}{m \times n}\right) \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} (f(x, y) - M)^2}$$

Support Vector Machine (Svm)

The original Support Vector Machine (SVM) algorithm, credited to Vladimir N. Vapnik, went through additional improvement by Cortes and Vapnik in 1993. This calculation, established in regulated learning methods, is flexible in its application, going from one-class grouping issues to n-class order issues. The center target of the SVM calculation is to address nonlinear order difficulties by changing them into straight changes through the usage of a portion capability, and in this review, we utilized the Gaussian piece capability. The classification procedure is made simpler by this transformation, which improves the separation of nonlinear samples or data. According to the study's definition, the SVM algorithm basically creates a hyperplane that effectively separates two training classes.

$$f(y) = Z^T \phi(y) + b$$

The SVM calculation's presentation can be assessed regarding exactness, awareness, and explicitness.

4. RESULT

To evaluate the viability of our calculation, we used two benchmark datasets alongside an extra dataset obtained from master radiologists. The last dataset included example pictures from 15 patients, each containing 9 slices, and was organized by master radiologists. The primary benchmark dataset, the Digital Imaging and Communications in Medicine (DICOM) dataset, this dataset needed ground truth images for approval. The subsequent benchmark, the Brain Web dataset, comprised of three-dimensional simulated brain MR information acquired from different modalities, including T1-weighted, T2-weighted, and proton density weighted MR images. This dataset used different constraints, for example, slice thickness, noise levels, and intensity nonuniformity. Expert radiologists provided the third dataset, which included ground truth images for comparison of results and 135 images from 15 patients across all modalities.

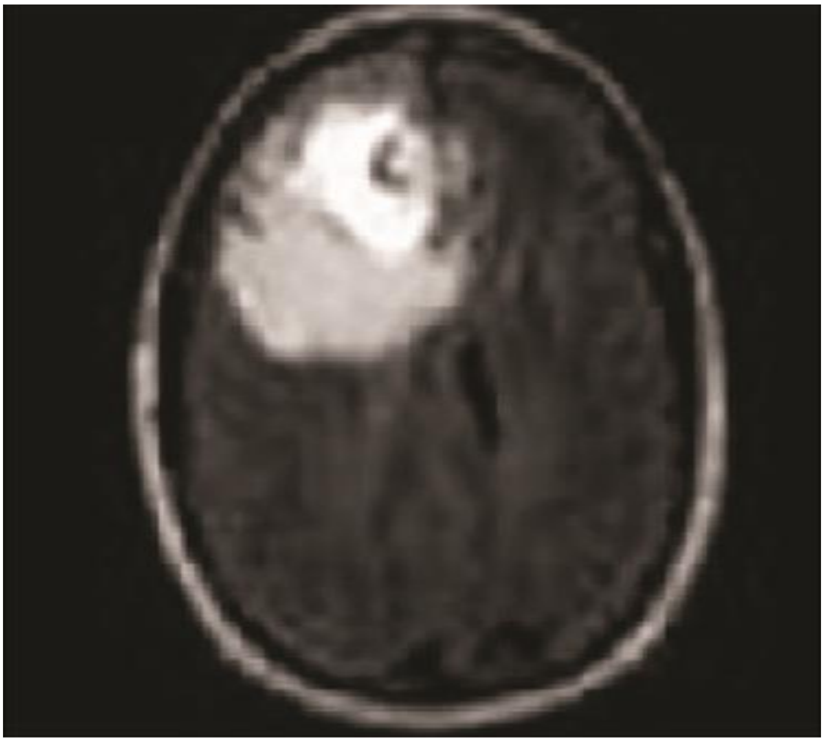

Figure 1. MRI scan showing Glioblastoma

The image segmentation proposed in this study was carried out utilizing Matlab 7.12.0 (R2011a), working on the Windows 8 platform with an Intel Core i3 processor and 4 GB RAM. The original image, enhanced image, skull-stripped image, wavelet decomposed image, cluster (intense) segmented image, dice overlap image, and the tumor region with extracted area marks are all shown in Figures 1, 2, and 3. Assessment measurements like Mean Squared Error (MSE), PSNR, and Dice coefficient were utilized. A lower MSE and higher PSNR demonstrate better sign to-commotion proportion, while the Dice coefficient estimates the cross-over among automatic and manual segmentation.

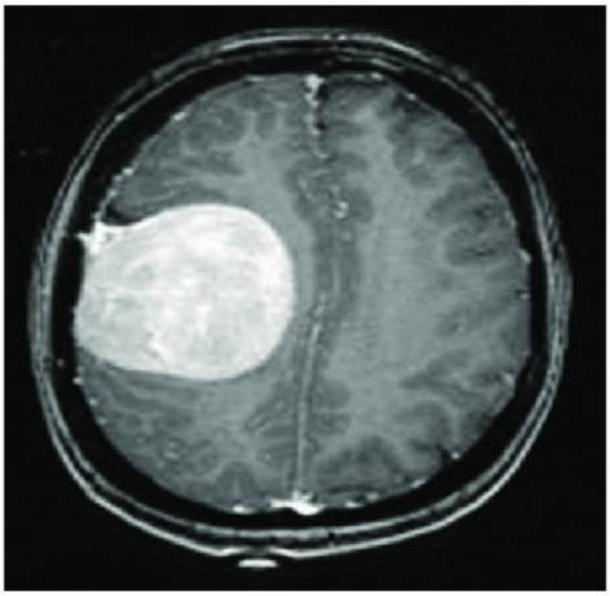

Figure 2. MRI scan in axial view showing the deformation of the brain structure due to a particularly infiltrating tumor mass

The k-Nearest Neighbours (k-NN), Support Vector Machine (SVM), Adaptive Fuzzy Inference System (ANFIS), and Back Propagation accuracy values, both with and without feature extraction are considered. Notably, feature extraction exhibited implementation improvement across all classifiers, upgrading tumor localization precision from brain MR pictures.

Our segmentation outranks cutting edge procedures, displaying predominant accuracy, sensitivity, and practically identical specificity. The significance of our proposed segmentation strategy in advancing brain tumour diagnosis from MR images is emphasized by the significant increase in sensitivity, which is especially important for radiologists and clinical doctors in surgical planning.

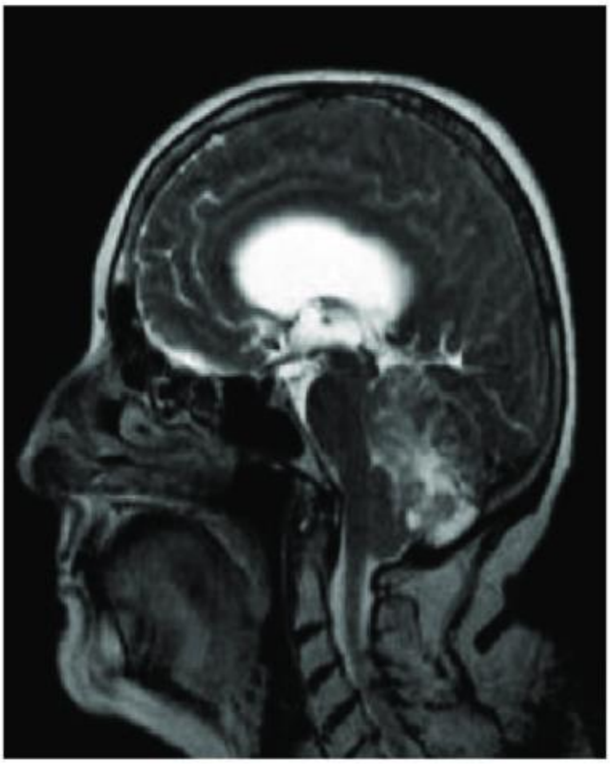

Figure 3. Saggital view of the infiltrating tumor mass shown in figure 2

5. CONCLUSION

In patients with glial tumors, this study focused on the segmentation of brain tissues in MR images, separating normal tissues (white matter, gray matter, cerebrospinal fluid - background) from tumor-infected tissues. Tumor-infected tissues included both benign and malignant stages. Images of fifteen patients were utilized in the review, adding to the examination. Preprocessing methods were utilized to improve the SNR and relieve the effect of undesirable clutter. An edge-based skull stripping algorithm was applied for further enhancing segmentation results, trailed by the use of the Berkeley wavelet change for picture division. The characterization of cancer stages was accomplished utilizing a Support Vector Machine (SVM), which examined highlight vectors and growth region.

The examination considered both texture based and histogram-based highlights, combined with a versatile classifier, for the tumor growth characterization in MR pictures. Experimental outcomes displayed the proficiency and exactness of the proposed calculation contrasted with manual recognition by radiologists or clinical specialists. Different execution measurements, including mean, Mean Squared Error (MSE), PSNR, accuracy, and Dice coefficient, showed the prevalent consequences of the proposed calculation. The proposed method's ability to distinguish between normal and abnormal tissues in MR images is demonstrated by its 96.51% accuracy. Based on these findings, it appears that the proposed approach has a significant amount of potential for integration into clinical result support systems, facilitating radiologists' or clinical experts' primary screening and diagnosis.

By investigating a selective scheme for the classifier, possibly combining multiple classifiers, and incorporating feature selection techniques, future efforts will focus on improving classification accuracy. This continuous investigation expects to additionally refine and upgrade the proposed approach for further developed brain tumor location and characterization in MR images.

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