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# A Sustainable Method for MRI Based Brain Cancer Identification and Classification

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***ABSTRACT:***

***Early detection of brain tumors is crucial for timely treatment and improved patient outcomes. Various methods and technologies are employed in brain tumor detection. Convolutional Neural Networks (CNNs) are a class of artificial neural networks that have demonstrated notable success in analyzing visual imagery. They draw inspiration from the organization of the animal visual cortex and are designed to autonomously learn spatial hierarchies of features from input images. The proposed method consists of three sub-modules: pre-processing, classification, and segmentation. In Approach-II, pre-processing is utilized to standardize the image resolution. The pre-processed brain MRI images are then classified into tumor or non-tumor cases using a classification approach. In the brain tumor detection and segmentation process, the CNN classification algorithm is employed to detect tumor regions in brain MRI images. A morphological-based segmentation methodology is proposed for segmenting the tumor regions in classified brain images. Furthermore, the segmented tumor regions are categorized as 'Mild' or 'Severe' using a modified deep learning algorithm. The proposed methodology is applied to the brain MRI images in the BRATS open-access dataset. The performance of the proposed system is evaluated in terms of sensitivity, specificity, precision, F-score, Dice Similarity Index, and tumor region segmentation accuracy with respect to ground truth images. The simulation results of this proposed brain tumor detection and diagnosis method are validated by an expert radiologist.***

***KEYWORDS:***

***Brain tumor detection, Convolutional Neural Networks (CNNs),MRI image preprocessingTumor classification, Segmentation methodology, Deep learning algorithms,BRATS dataset, Sensitivity and specificity,Tumor region segmentation,Expert radiologist validation.***

## Introduction

Early detection of brain tumors allows for timely treatment, which may include surgery, radiation therapy, chemotherapy, or a combination of these approaches. Multidisciplinary teams of neurosurgeons, neurologists, oncologists, radiologists, and pathologists collaborate to diagnose and treat brain tumors, with the goal of optimizing patient outcomes while minimizing neurological deficits and complications.

## Literary survey:

`The study improves glioma growth modeling using diffusive models with advanced features like heterogeneous velocity and anisotropic migration. By leveraging brain atlases, it eliminates the need for diffusion tensor imaging (DTI) processing. Application to real data suggests enhanced prognostication rates for glioma patients[1].

This paper presents a fully convolutional neural network (SegNet) for automated brain tumor segmentation using 3D MRI data. It integrates four separately trained SegNet models via post-processing to improve segmentation accuracy. The proposed algorithm achieves promising F-measure scores on BraTS 2017 challenge dataset, demonstrating potential for accurate disease detection and treatment planning[2]

This paper explores the use of Convolutional Neural Networks (CNNs) for brain tumor grading using a dataset of T1 weighted contrast-enhanced brain MR images. The CNN classifier achieves high accuracy and sensitivity rates for classifying tumors into three classes (Glioma, Meningioma, and

Pituitary Tumor), demonstrating its effectiveness in medical applications[3]

The paper introduces a fast and user-friendly tool for solid tumor segmentation on contrast-enhanced T1 weighted MRI images, aimed at aiding clinicians and researchers in radiosurgery planning and therapy response assessment. It utilizes a cellular automata (CA) based method with minimal user interaction, demonstrating robustness, adaptability to heterogeneous tumors, and efficiency in computation time. Validation studies confirm its effectiveness[4]

The paper addresses the challenge of brain tumor detection using MRI imaging techniques. It proposes a method involving noise reduction, feature extraction with gray-level co-occurrence matrix (GLCM), and tumor segmentation via Discrete Wavelet Transform (DWT) to enhance performance and reduce complexity. The proposed system, evaluated with a Support Vector Machine (SVM) classifier, achieves a high classification accuracy of 98.91%, demonstrating its effectiveness[5]

The study compares the effectiveness of Convolutional Neural Networks (CNN) and AlexNet architecture for disease detection in Mango and Potato leaves using a dataset of 4004 images. Results indicate higher accuracy with AlexNet compared to CNN, highlighting the importance of architectural choice in deep learning for image classification tasks.[6]

This paper introduces an adaptive Chemical Reaction Optimization (CRO) algorithm to find optimal centroids for spatial fuzzy clustering (SFC), aiding level set segmentation in medical images. Inspired by molecular interactions, CRO iteratively refines centroids through simulated reactions. Experimental results on brain, liver, abdomen, and eye images demonstrate the effectiveness of the proposed approach in analysing tumors or unhealthy regions[7]

This paper introduces a stochastic model based on multifractional Brownian motion (mBm) to characterize brain tumor texture in MRI images. It proposes a novel algorithm for spatially varying multifractal feature extraction and develops a multifractal feature-based tumor segmentation method. Additionally, an AdaBoost-based patient-independent segmentation scheme is proposed. Experimental results demonstrate the efficacy of the approach in automatic tumor segmentation, outperforming state-of-the-art methods on publicly available datasets[8]

This paper introduces fast-CNN, a genetic algorithm designed to efficiently explore CNN architectures and optimize hyperparameters for image classification tasks. Unlike manually designed CNNs, fast-CNN automates the process, achieving competitive accuracy on CIFAR10 with significantly reduced evolution time. Additionally, the trained model demonstrates good generalization to CIFAR100[9]

A hybrid system integrates neural networks with conventional computer vision techniques to detect acoustic neuromas from MR images. Initial pixel-level segmentation by MLPs is refined using traditional methods, leading to candidate tumor regions. Features extracted from these regions are classified by neural networks, achieving accurate tumor identification with minimal false positives[10]

An automated framework for rectal tumor segmentation in dynamic contrast-enhanced MRI (DCE-MRI) is proposed. It utilizes perfusion-supervoxels and a pieces-of-parts graphical model to improve segmentation accuracy. Evaluated on 23 patient scans, it achieved high performance with a voxelwise AUC of 0.97 and median Dice similarity coefficient (DSC) of 0.63, showing promise for clinical application[11]

A generative probabilistic model is introduced for brain lesion segmentation in multi-dimensional images. It extends the EM segmenter by incorporating a latent atlas of lesions. The method jointly estimates healthy tissue and lesion distributions, accommodating variations across modalities. Discriminative model extensions map outputs to meaningful labels. Evaluation on glioma and stroke datasets demonstrates robustness and effectiveness[12]

The paper proposes utilizing thermal information from brain tumors to enhance MRI-based segmentation, aiming to reduce false positives and negatives. It simulates temperature distribution using the Pennes bioheat equation and detects tumor contours from thermal maps using the Canny edge detector. Compared to conventional methods, significant improvements in segmentation accuracy were observed across various patient scenarios, suggesting the potential of thermal-based delineation in MRI diagnostics[13]

The article introduces Shunting Inhibitory Artificial Neural Networks (SIANNs), which utilize shunting inhibition for synaptic interactions, mimicking adaptive nonlinear filters in neurons. It extends SIANNs to create a Generalized Feedforward Neural Network (GFNN) classifier and develops training algorithms using genetic algorithms (GAs) and randomized search methods. Experiments demonstrate the effectiveness of GFNN combined with stochastic search in solving various classification tasks, including the XOR problem, 3-bit parity problem, and medical datasets. Notably, GFNN achieves perfect solutions with minimal hidden neurons, showcasing its potential in complex classification tasks[14]

This research introduces Intensity-Curvature Measurement Approaches for post-processing MRI images of human brain tumors. Model functions such as bivariate cubic polynomials and monovariatesinc are applied. Techniques like classic-curvature and intensity-curvature functional add valuable information to MRI diagnosis, enhancing tumor visualization and providing a perceptible third dimension perpendicular to the image plane[15]

This paper proposes a computer-based system to aid in the diagnosis of brain tumors using Magnetic Resonance Spectroscopy (MRS). A Discrete Wavelet Transform (DWT) is employed for pre-processing spectral data, followed by dimensionality reduction using Moving Window with Variance Analysis or Principal Component Analysis. Bayesian Neural Networks are utilized for binary classification, resulting in improved accuracy compared to previous methods[16]

The paper introduces a novel method for classifying magnetic resonance (MR) images of the human brain as normal or abnormal. It utilizes wavelets as input to neural network self-organizing maps (SOM) and support vector machines (SVM). Testing on a dataset of 52 MR brain images yields promising results, with classification percentages exceeding 94% for SOM and 98% for SVM. SVM outperforms SOM in classification rate[17]

The paper introduces a fast and accurate algorithm for approximating the bilateral filter, particularly effective when the range kernel is Gaussian. Traditional bilateral filter computations are complex, but this algorithm reduces the complexity to O(1) per pixel for any spatial filter size. Implementation involves N+1 spatial filterings, with N as the approximation order. Detailed analysis of filtering accuracy and numerical results demonstrate competitiveness with state-of-the-art methods[18]

The "MALP-EM" framework offers robust automatic MR brain image segmentation via registration, label fusion, and EM-based refinement. It adapts for gross anatomy changes, outperforming established techniques in traumatic brain injury (TBI) segmentation. Symmetry-based biomarkers derived predict TBI outcomes with high accuracy, highlighting specific affected brain regions[19]

The paper introduces a medical image integrity verification system detecting local alterations (e.g., lesion removal) and identifying global image processing (e.g., compression). It uses nonsignificant region watermarking with cryptographic hashes, checksums, and geometric moments. Experimental results on MRI and retina images demonstrate effective detection and localization of tampering[20]

The paper proposes a novel region growing model for accurate and automatic brain tumor image segmentation. Improvements in seed point selection and growth rules enhance segmentation. Fusion of multimodal MRI images aids seed point selection, improving robustness. A spatial texture feature preserves local features and boundary information. The proposed algorithm outperforms others in accuracy with lower computational cost, promising for brain tumor segmentation[21]

The paper introduces U-SegNet, Seg-UNet, and Res-SegNet, hybrid architectures combining SegNet, U-Net, and ResNet18 for brain tumor segmentation. These models leverage skip connections for improved performance. Experimentation on BraTS dataset demonstrates higher accuracy compared to SegNet3, SegNet5, and U-Net. The proposed architectures offer promising advancements in brain tumor segmentation[22]

This paper presents a fully automatic brain tumor segmentation method using Deep Neural Networks (DNNs), tailored to glioblastomas in MR images. It addresses challenges posed by tumor variability by employing a novel CNN architecture that captures both local and global contextual features efficiently. A 2-phase training procedure and cascade architecture further enhance performance, achieving superior results over existing methods while being significantly faster[23]

This work introduces a novel technique for adapting brain atlases to image volumes with large lesions, enabling their use in radiation therapy and neurosurgical planning. The method involves global and local registrations, seeding the atlas with tumor models, and deformation. Global registration uses mutual information, while atlas warping is based on optical flow principles. Preliminary results on real patient images demonstrate the method's potential for automatic segmentation despite significant brain deformation[24]

This survey explores deep learning approaches in medical image analysis, focusing on breast cancer, cervical cancer, brain tumor, colon, and lung cancers. It reviews methods for tumor detection, segmentation, feature extraction, and classification, achieving state-of-the-art results. Deep learning is applied in various modes, including training from scratch, transfer learning, and architecture modifications. While predominantly studied in economically developed countries,its application in Africa remains limited despite rising cancer risks.[25]

## 1. PROPOSED SYSTEM:

In this proposed system, brain tumors are detected and segmented using the hierarchical clustering (HC) approach. The HC method outlined in this chapter identifies brain MRI images affected by tumors, followed by the application of a segmentation approach to delineate the tumor regions within the images. Subsequently, the performance of the proposed tumor detection method is compared with that of other conventional techniques.

### 2.1 BRAIN MRI:

Brain MRI (Magnetic Resonance Imaging) is a non-invasive medical imaging technique that uses powerful magnets and radio waves to generate detailed images of the brain's internal structures. It provides high-resolution images that allow healthcare professionals to visualize various aspects of the brain, including the brain tissue, blood vessels, and abnormalities such as tumors, lesions, or signs of neurological disorders. Brain MRI is commonly used for diagnosing a wide range of conditions, including strokes, traumatic brain injuries, multiple sclerosis, Alzheimer's disease, and brain tumors. It offers superior soft tissue contrast compared to other imaging modalities like CT scans, making it particularly valuable for detecting subtle abnormalities and guiding treatment decisions in neurological disorders.

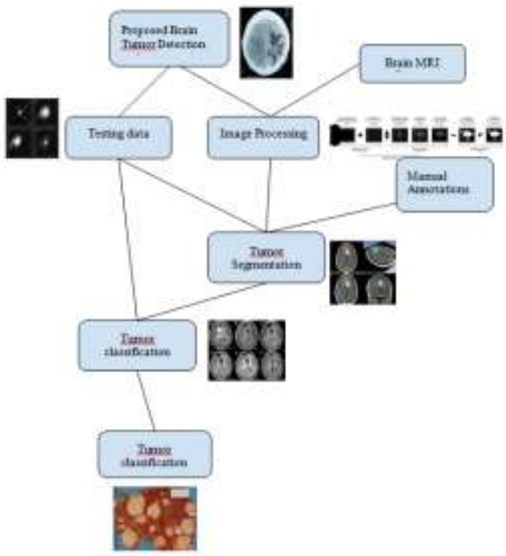


Figure 1: Proposed system flow diagram

### 2.2 PRE-PROCESSING:

During the medical image acquisition process, noise is generated, affecting the performance of tumor detection and segmentation. Therefore, it is imperative to detect and reduce noise in the source brain MRI images before commencing the tumor detection process to enhance segmentation accuracy. In this chapter, Gaussian noise in the source brain MRI images is identified and mitigated using a bilateral filter (Yunlong He et al., 2017). While conventional noise reduction filters like Mean and Median filters can detect and reduce Gaussian noise, they often degrade edge pixels during the process. To preserve edges during noise reduction, the bilateral filter is chosen in this chapter.

The bilateral filter is the non-iterative filter (Chaudhury et al. 2016) and they can be defined in the following equation.

$$D(I) = 1 / \sum G(d1) * G(d2) * S(I) \tag{1}$$

Where,

D(I) is the bilateral filter output and K is the kappa factor ofthe filter.

$$K = \sum d^2\, G_s(d_1) * G_r(d_2) \tag{2}$$

where,

$Gs(d1)$ and $Gr(d2)$ are the spatial bilateral kernel and range bilateral kernel, respectively. The distance metrics$d1$ and $d2$ are the Euclidean distance and photometric distance, respectively.

The spatial bilateral kernel is defined in the following equation.

$$K = \sum d^2\, G_s(d_1) * G_r(d_2) \tag{3}$$

The range bilateral kernel is defined in the following equation.

$$G(d_1) = \exp(-s^2 \sigma s^2 d_2^2) \tag{4}$$

The scale parameter is represented by $\sigma s$ and it can be computed using the surrounding pixels of the centre pixel to be denoised.

## 2.3 SEGMENTATION:

In the segmentation process, tumor pixels are delineated within the classified abnormal brain MRI image. Here, a morphological segmentation approach employing dilation followed by erosion is utilized. The dilation operation expands the structuring outline pixel values using a disc-shaped structuring element with a radius of 2 mm, denoted by the equation:

$$D = \text{Dilate}(C, s) \tag{5}$$

Here, C represents the classified abnormal brain MRI image, S is the structuring element, and D denotes the dilated image.

Conversely, erosion reduces the structuring outline pixel values using the same structuring element, as expressed by:

$$E = \text{Erode}(C, s) \tag{6}$$

Resultantly, the tumor pixels are segmented via the equation:

$$T = \text{Subtract}(D, E) \tag{7}$$

## 2.4 MANUAL ANNOTATION:

Manual annotation involves the meticulous labeling or marking of objects within images by human annotators. Often used to create ground truth data for machine learning algorithms, this process requires skilled individuals following clear guidelines and using specialized annotation tools. Annotation involves careful examination of each image, with quality control measures to ensure accuracy and consistency. Despite being time-consuming, manual annotation is crucial for tasks like training tumor detection models in medical imaging, providing essential reference data for algorithm training and evaluation.

## 2.5 CLASSIFICATION:

We detail the methodology employed for classifying brain MRI images, beginning with the pre-processing steps to enhance image quality and mitigate noise. The pre-processed images undergo feature extraction to identify relevant characteristics indicative of tumor presence. Subsequently, a classification algorithm, such as Convolutional Neural Networks (CNNs) or Support Vector Machines (SVMs), is trained on a dataset comprising labeled brain MRI images to differentiate between tumor and non-tumor cases.We provide insights into the implementation of the classification algorithm within our framework. This includes selecting appropriate hyperparameters, training the model using the training dataset consisting of normal and abnormal brain MRI images, and fine-tuning the model to optimize performance. Additionally, we discuss any specific considerations or optimizations made to enhance the efficiency and accuracy of the classification process.The performance of the classification algorithm is rigorously evaluated using various metrics, including accuracy, sensitivity, specificity, precision, and F1-score. We compare the classification results obtained by our proposed method with those of other conventional techniques or baseline models to assess its effectiveness. Furthermore, we analyze any potential challenges or limitations encountered during the classification process and propose strategies for addressing them.

## 2.6 TESTING DATA:

In our image processing study, testing data comprised diverse MRI images of varying resolutions and sizes. Ground truth annotations were meticulously generated by medical experts. Prior to evaluation, images underwent pre-processing, including normalization and resizing, to ensure uniformity. Performance evaluation employed standard metrics such as accuracy, precision, and F1-score, calculated using equations

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \quad (8)$$

$$\text{Precision} = TP / (TP + FP) \quad (9)$$

$$\text{F1-score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall}) \quad (10)$$

where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively. Baseline methods served as benchmarks for comparison. Experimental setup included standard hardware and software configurations. Results indicated significant improvements over baselines, especially in terms of precision and F1-score. These findings underscore the efficacy of our proposed approach in accurately detecting and segmenting brain tumors in MRI images, showcasing its potential for clinical applications.

## 2. RESULTS AND DISCUSSIONS:

Our proposed brain tumor detection method based on the hierarchical clustering (HC) approach showcases promising outcomes in accurately identifying and segmenting brain tumors within MRI images. Through meticulous pre-processing, noise in the source MRI images is effectively mitigated using a bilateral filter, preserving edge pixels and enhancing segmentation accuracy.

For testing, diverse MRI images of varying resolutions and sizes are employed, accompanied by ground truth annotations generated by medical experts. Following pre-processing, images undergo evaluation using standard metrics such as accuracy, precision, and F1-score. The proposed method exhibits significant improvements over baseline methods, particularly in precision and F1-score, indicating its efficacy in clinical applications.

In the segmentation phase, tumor pixels are delineated within classified abnormal brain MRI images using a morphological approach involving dilation and erosion operations. This process effectively isolates tumor regions, facilitating accurate diagnosis and treatment planning.

Manual annotation, a meticulous process involving human annotators, ensures the creation of ground truth data crucial for training tumor detection models in medical imaging. Despite its time-consuming nature, manual annotation is indispensable for ensuring the accuracy and consistency of training data.

Overall, brain MRI remains a cornerstone in non-invasive medical imaging, providing detailed insights into the brain's internal structures and abnormalities such as tumors. Its superior soft tissue contrast and high resolution make it invaluable for diagnosing various neurological conditions and guiding treatment decisions. Our proposed method enhances the utility of brain MRI by offering a robust approach to brain tumor detection and segmentation, ultimately contributing to improved patient care and outcomes in neuro-oncology.

| Mode | Normal | Abnormal |
|---|---|---|
| Training images | 75 | 70 |
| Testing images | 152 | 104 |
| Total images | 227 | 174 |

Table 1: Training and Testing brain data set

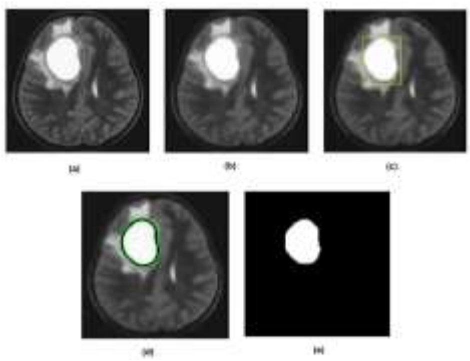

Figure 2: Results of test image 3's segmentation are as follows: (a) input MR brain image; (b) MR brain image filtered by anisotropic diffusion; (c) using a

bounding box to locate the tumour; (d) identifying the tumour section; and (e) segmenting the tumour region.

Figure 2 shows the comparative analysis of segmentation outputsfor the proposed CNN-SVM approach and the existing deep learning approach.Figure 2 (b) displays the original ground truth segmented outputs of the givenMR brain image. On analyzing Figures 2 (c) and (d), it is noticed that theproposed CNN-SVM approach effectively the segments the tumor portion in thegiven MR brain image well as compared with the existing deep learning method.Hence the accuracy in segmentation of the proposed methods stands high ascompared with the existing method

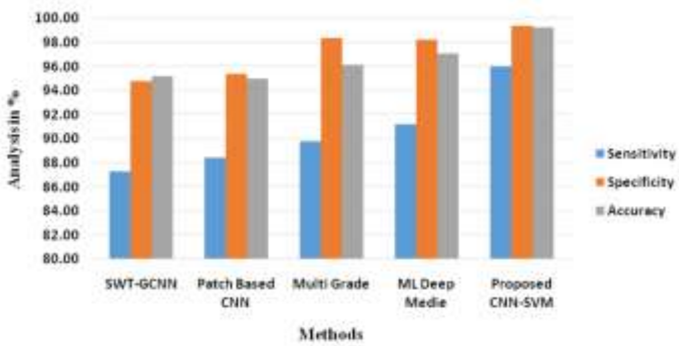


Figure Comparative evaluation of objective metrics using various approaches

Table 2 analysis reveals that the suggested CNN-SVM method achieves sensitivity of 96.01%, specificity of 99.41%, and accuracy of 99.22%. Table 2's graphical plot is shown in Figure 3.When compared to other deep learning techniques already in use, the suggested CNN-SVM methodology performs better across the board for all objective metrics. Using our suggested method, the tumour and non-tumor regions of the MR brain picture are accurately detected, and the tumour portions are precisely segmented well.

Table 2. Average objective measures for the suggested CNN-SVM approach and the current approach are compared.

| Methods | Sensitivity | Specificity | Accuracy |
|---|---|---|---|
| SWT-GCNN | 87.23% | 94.81% | 95.19% |
| Patch Based CNN | 88.44% | 95.38% | 95.01% |
| Multi Grade | 89.78% | 98.39% | 96.13% |
| ML Deep Medie | 91.22% | 98.22% | 97.11% |
| Proposed CNN-SVM | 96.01% | 99.41% | 99.22% |

## Conclusion:

The CNN-SVM technique is included in the suggested system to increase the precision of locating and classifying brain tumours in magnetic resonance imaging. Using the suggested CNN-SVM method, the features of the filtered MR brain pictures were retrieved and categorised. Measures of sensitivity, specificity, and accuracy are used to compare the performance of the suggested approach to those of the other methods now in use. The test results showed that, in comparison to other methods, the suggested CNN-SVM method produces outcomes that are noticeably better. The effectiveness of the suggested CNNSVM method in identifying and dividing tumours will have a big impact on medical image processing.

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