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Segmentation of brain tumor in MRI using AI assistedActive region contour model

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Abstract
The application of Active Region Contour Models (ARCMs) is a sophisticated method for precisely delineating brain tumors in MRI images. ARCMs, also known as active contours or snakes, dynamically evolve over the images, adapting to tumors' complex and irregular shapes. The segmentation process involves the initiation of a contour near the tumor boundaries, followed by iterative adjustments guided by internal and external forces. These contours' "active" nature allows them to handle intensity variations within MRI images, a common challenge in tumor imaging.This article explores the integration of artificial intelligence (AI) with the active region contour model, presenting an innovative approach that combines the adaptability of active contours with the power of AI for more precise and efficient brain tumor segmentation in MRI.

1. Introduction

Medical imaging has changed the face of modern healthcare by delivering non-invasive insights into the human body's complex architecture and function. Magnetic resonance imaging (MRI) is a sophisticated diagnostic tool that produces detailed images of soft tissues, including the brain. Brain tumor segmentation in MRI has been a focus of research and technological improvements, with the quest of more accurate and economical techniques driving continuous innovation [1], [2]. Brain tumors, which are defined by abnormal cell proliferation inside the brain, pose a substantial problem in the medical world[3]. The accurate segmentation of these tumors is critical for precise diagnosis, therapy planning, and patient monitoring. While the human brain's complexity makes this task difficult, technology advancements have opened the path for advanced segmentation approaches.Traditional techniques of brain tumor segmentation have difficulty reliably identifying tumor borders, particularly in situations with irregular forms and varied intensities[4]. Manual segmentation, while precise, is time-consuming and prone to inter-observer variability. Automated approaches have consequently become critical to expedite the segmentation process and improve repeatability.

MRI, with its exceptional capacity to obtain exquisite soft tissue pictures, has emerged as the preferred technique for visualizing brain tumors[5]. The intrinsic contrast of MRI provides for obvious separation between tumor and healthy tissue, making it an excellent choice for segmentation investigations. However, the various nature of brain tumors, including changes in size, form, and location, needs improved tools for precisely defining tumor borders.Magnetic resonance imaging (MRI) outperforms computed tomography in the realm of medical diagnostics compared. Imaging enhances the contrast between various soft tissues in the human body. Due to its advantages in terms of safety and tissue contrast, MRI is the most used technology in brain imaging when compared to other modalities[6]. Many efforts have been made in recent years to develop human-free intervention approaches that can produce results equivalent to those obtained by physicians. A variety of supervised and unsupervised learning approaches have been explored for this aim [7]–[13].

The segmentation process usually starts with the creation of a contour near the probable tumor boundaries. This active contour then iteratively modifies its shape using a combination of internal pressures that promote smoothness and external forces that guide the contour towards the tumor margins. The continuous evolution of ARCMs provides flexibility, making them ideal for capturing the abnormalities commonly found in brain tumor borders.

Active region contour models are deformable curves that evolve based on the minimization of an energy functional. The driving force behind their efficacy lies in the ability to adapt to image features, making them particularly well-suited for capturing intricate boundaries within medical images. The models operate

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through an iterative process, adjusting their contours to minimize internal and external energies, facilitating precise segmentation.Active contour models are deformable, curve-evolving algorithms that minimize an energy functional. They adapt to image features, making them well-suited for capturing intricate boundaries of brain tumors. The models operate through an iterative process, adjusting the contour to minimize internal energy (encouraging smoothness) and external energy (driving the contour toward image features)[14]. At the center of active region contour models is an energy functional that includes both internal and exterior elements. Internal energy measures contour smoothness, which helps to prevent segmentation abnormalities. External energy from picture features or gradients directs the contour toward the image's important limits. This dynamic interaction guarantees that the contour converges on the target structures, allowing for precise and adaptable segmentation[15]–[17].

The emergence of artificial intelligence, particularly deep learning, provides new avenues for enhancing the accuracy and efficiency of segmentation. This article explores the integration of AI with the active region contour model, presenting a cutting-edge approach that leverages the strengths of both methodologies. AI, particularly deep learning techniques like convolutional neural networks (CNNs), excels in feature extraction and pattern recognition[18]. By leveraging a CNN, the segmentation model can autonomously learn complex patterns and relevant features from the MRI data, enhancing the capability to distinguish tumor boundaries from surrounding tissues[19].The AI component introduces dynamic mask updating, continuously adapting the pre-fitting mask based on learned features. This addresses challenges associated with static masks, ensuring the segmentation model remains adaptable to evolving tumor characteristics throughout the segmentation process.AI assists in refining the initialization process, optimizing the starting point for the active contour model. Additionally, AI-driven algorithms contribute to more efficient convergence, overcoming challenges related to sensitivity to parameters and speeding up the segmentation workflow.

In this paper, we provide a region-based active contour approach for automated brain tumor extraction from MR images. In general, brain tumor extraction from MR images using active contours requires the identification of a starting contour, which is challenging to achieve automatically, particularly in tumors with poor contrast and uncertain borders. To address the issue, we employed AI to determine the beginning boundary of the active contour method. Section 2 of the paper represents the mathematical formulation of the region based active contour model and section 3 of the paper shows the AI assisted methodology in creating the initial mask of the active contour. The proposed methodology and validation are shown in section 4. The results are shown in section 5 and section 6 concludes the research study.

2. Region based active contour model

The Region-Based Active Contour Model is a mathematical framework for image segmentation and object boundary delineation. It's also referred to as a region-based level set or geodesic active contour model. As per[20]the energy functional can be represented as,

$$E(C, c_1, c_2) = \lambda_1 \int_{\text{outside } C} \|I(x) - c_1\|^2 dx + \lambda_1 \int_{\text{inside } C} \|I(x) - c_2\|^2 dx + \nu|C| \quad (1)$$

Here $I(x): \Omega \to \Re^d$ is an image defined on domain Ω and the constants c_1 and c_2 approximates the image intensity inside and outside of the contour C with a length |C|. As per [21], the contour C can be represented in the image plane ($\Omega \to \Re^d$) as the zero level of an embedding Lipschitz-continuous function, $\phi: \Omega \to R$, defined in a higher dimension, i.e. $C = \{x \in \Omega | \phi(x) = 0\}$. By minimizing using the steepest descent method, we can state that,

$$\frac{\partial \phi}{\partial t} = |\nabla \phi| \left\{ \lambda_1 (I - c_1)^2 + \lambda_2 (I - c_2)^2 + \mu . \operatorname{div}\left(\frac{\nabla \phi}{|\nabla \phi|}\right) - \nu \right\} \quad (2)$$

Where

$$c_1 = \frac{\int_\Omega IH(\phi) d\Omega}{\int_\Omega H(\phi) d\Omega} \quad (3)$$

$$c_2 = \frac{\int_\Omega I(1 - H(\phi)) d\Omega}{\int_\Omega (1 - H(\phi)) d\Omega} \quad (4)$$

The Heaviside function $H(\phi)$ and the delta function $\delta(\phi) = H'(\phi)$ can be approximated as

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$$H_\varepsilon(\phi) = \frac{1}{2}\left(1 + \frac{2}{\pi}\tan^{-1}\left(\frac{\phi}{\varepsilon}\right)\right) \qquad (5)$$

$$\delta_\varepsilon(\phi) = \frac{1}{\pi}\frac{\varepsilon}{\varepsilon^2+\phi^2} \qquad (6)$$

where is εa constant that has been set to 1.0[22]. Here the model follows an iterative optimization procedure in which the contour evolves to minimize the defined energy. Internal energy promotes smoothness and prevents irregularities, but external energy, generated from image gradients or features, draws the contour to the object borders. This energy reduction guarantees that the contour converges with the required structure, maximizing its representation inside the image.The adoption of an initial mask is an important step in the implementation of active contour area models, notably in medical picture segmentation. The initial mask serves as a starting point for the iterative optimization process, directing the contour toward the borders of the item of interest. In the setting of medical imaging, when precise delineation is critical, creating an effective initial mask becomes an essential part of the segmentation procedure. I'll go over the necessity of the first mask, techniques for creating it, and factors to consider ensuring its efficacy.

3. Initial mask generation using AI

The initial mask functions as a seed or region of interest, influencing the development of the active contour. A well-designed initial mask has a substantial influence on convergence speed, segmentation accuracy, and the model's capacity to adapt to complicated structures in an image. In medical imaging, where the aim is frequently to segment certain anatomical features or anomalies, the initial mask is critical in directing the active contour to the right bounds.Accurate initialization is required for active region contour models to converge on the genuine tumor borders. Traditional approaches frequently use manual or semi-automatic initialization, which can be time-consuming and subjective. Inaccuracies in initialization can result in inferior segmentation outcomes, reducing the models' reliability in clinical applications.The integration of AI into the segmentation pipeline introduces a transformative solution to the initialization challenge. Machine learning models, particularly convolutional neural networks (CNNs), are trained on annotated MRI data to learn patterns and features indicative of brain tumor locations[18]. The trained model performs feature extraction on new MRI data, generating a probability map that highlights potential tumor regions[23]. By applying thresholding to this map, binary masks are created, serving as the AI-generated initial approximation of the tumor region.

4. Propose methodology and validation

The proposed methodology consists of multiple steps. First, MRI data is gathered and pre-processed to ensure image uniformity and quality[24]. Next, a CNN is trained on annotated data to learn the intricate patterns associated with brain tumors[23]. A probability map is created by extracting features from new MRI data. This map is then thresholded to produce binary masks[23], which comprise the AI-generated initial masks. These masks are smoothly integrated into the active region contour model, resulting in a more informed segmentation process.The fidg. 1 shows the schematic representation of AI assisted active contour model (ACM).

Dice similarity coefficient [25] and Sensitivity (SE) are examinedto validate the proposed methodology. The Dice and sensitivity are defined as follows:

$$\text{Dice} = \frac{2TP}{2TP+FP+FN} \qquad (7)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \qquad (8)$$

Here, TP and TN represent True Positive i.e. existing tumour that was accurately identified and True Negative i.e. tumour that did not exist but was detected, respectively. FP and FN represent False Positive i.e. detection of previously undetected tumour and False Negative i.e. existing tumour that has not been detected, respectively.

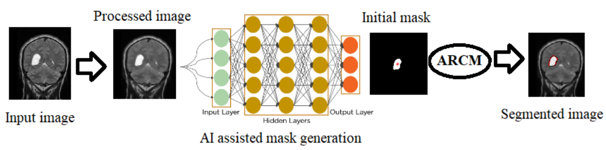

Fig 1. Schematic representation of proposed AI assisted active contour model

5. Results and discussion

The use of an active area contour model with AI assisted initial mask generation to segment brain tumors in MRI is a significant improvement in medical image analysis. This novel technique combines the flexibility of dynamic contour models with the precision of pre-

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fitting masks, providing a nuanced answer to the issues of brain tumor segmentation. The proposed methodology is tested with the MRI images as shows in fig 2. The input MRI is shown in fig. 2(a) The image is pre-processed with median filter and the filtered image is shown in fig. 2(b). Fig. 2(c) is the initial mask generated using AI assisted methodology. In fig. 2(d), the centroid of the initial mask is shown in the input image which is generated using AI assisted method. The initial active contour is shown in fig. 2(e-i) for an arbitrary mask and the evolution of the contour are shown in fig. 2(e-ii) – 2(e-iv) for increasing iteration.The initial contour using proposed methodology around the centroid is shown in fig. 2(f-i) and the evolution of the contour are shown in fig. 2(f-ii) – 2(f-iv) for increasing iteration. It is easy to see that the using proposed methodology, the efficiency of active region contour model is much better than the considering any arbitrary initialization of contour.

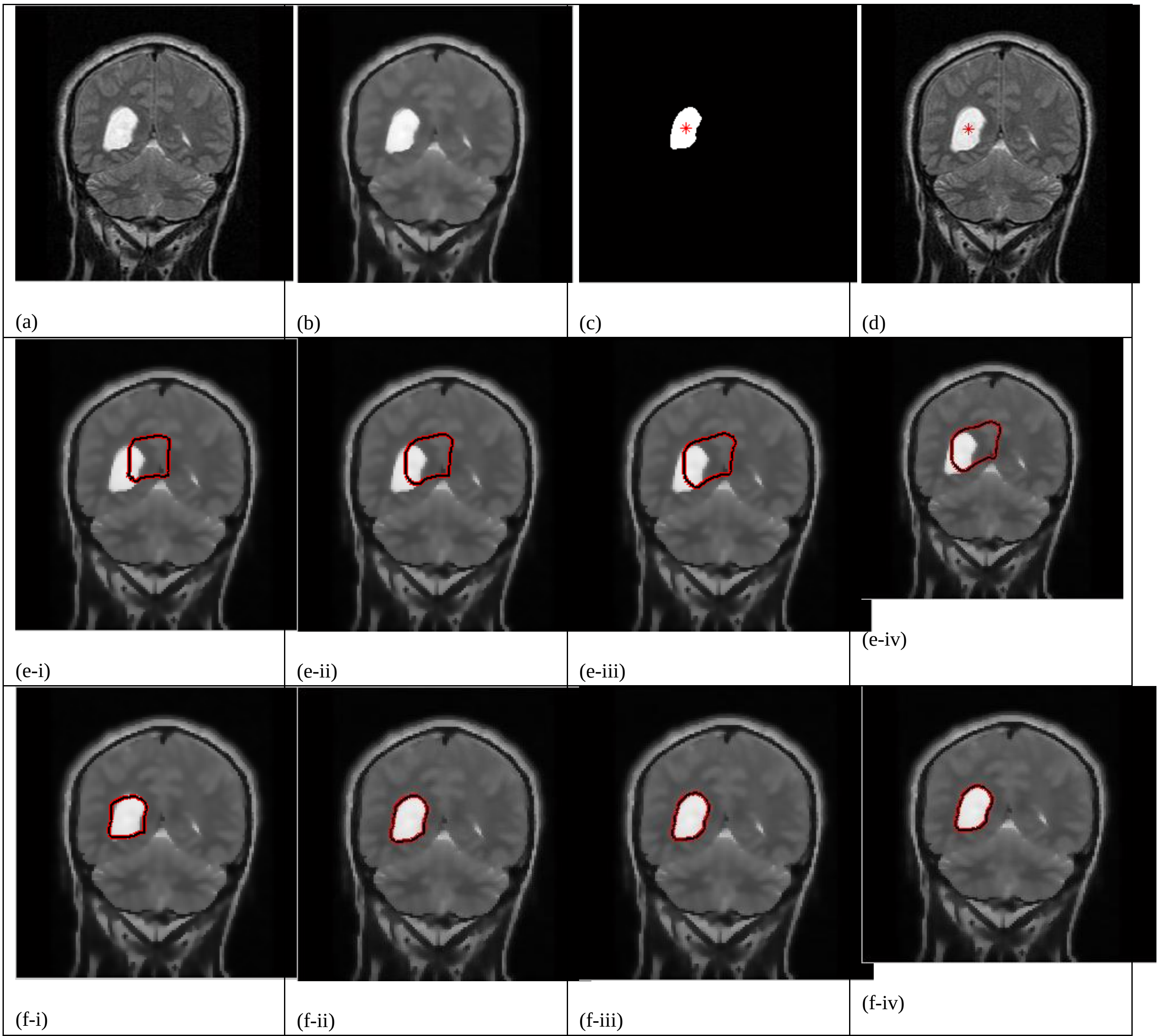

Fig 2.(a) input MRI (b) filtered using anisotropic diffusion (c) initial mask and center of the mask using proposed methodology (red dot) (d) centroid of mask in input image (e-i) initial contour using arbitrary mask (e-ii)-(e-iv) represents the evolution of contour in iteration 2, 6, 8, 10, 12, 14; (f-i) initial contour using proposed methodology and (f-ii)-(f-iv) represents the evolution of contour in iteration 4, 8, 12, 16.

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The BraTS 2015 dataset is useful for segmenting images of brain tumors[26]–[30]. The collection includes 54 low-grade gliomas (LGG) and 220 high-grade gliomas (HGG). HGG and LGG data from the 2015 BRATS dataset are used to validate the suggested technique. The proposed AI assisted method is compared with the k-means methods of initial mask generation and the performance are shown in Table I.

Table I: Average (±S.D.) of the similarity metrics for the proposed AI assisted method and using active contour model with k-means

Active Contour model with	Dice	Sensitivity	Average number of iterations
k-means	0.8979±0.025	0.8857±0.074	28±3
Proposed method	0.9019±0.031	0.9037±0.085	17±7

The integration of AI assisted initial mask generation into the segmentation process addresses one of the longstanding challenges in medical image analysis — the need for accurate initialization. The use of AI-generated first masks has various benefits. For starters, it considerably decreases the need for manual or semi-automatic initialization approaches, which streamlines the segmentation procedure. Second, the AI-driven approach takes advantage of neural networks' innate capacity to detect complicated patterns, increasing the accuracy of the initial masks. Third, the methodology is applicable to diverse tumor forms and imaging circumstances, making it a flexible option for a variety of clinical contexts. Quantitative metrics, such as the Dice coefficient and sensitivity, are employed to evaluate the performance of the proposed methodology. Comparisons with traditional methods are made to showcase the superiority of the AI-assisted active region contour model in terms of segmentation accuracy and efficiency.

6. Conclusion

The integration of AI for the generation of initial masks for active region contour models represents a significant advancement in the field of brain tumor segmentation. This collaborative approach addresses the longstanding challenge of accurate initialization, providing a more precise and efficient means of delineating tumor boundaries in MRI. As technology continues to evolve, this methodology stands at the forefront of innovations in medical image analysis, offering a promising avenue for improved diagnostic capabilities and patient care in neuroimaging. The symbiosis between AI and active region contour models signifies a paradigm shift, marking a new methodology in the quest for more accurate and reliable brain tumor segmentation techniques.

References

1. R. Wang, T. Lei, R. Cui, B. Zhang, H. Meng, and A. K. Nandi, “Medical image segmentation using deep learning: A survey,” IET Image Process., vol. 16, no. 5, pp. 1243–1267, 2022.
2. C. L. Chowdhary and D. P. Acharjya, “Segmentation and Feature Extraction in Medical Imaging: A Systematic Review,” Procedia Comput. Sci., vol. 167, pp. 26–36, 2020.
3. J. H. Sampson, M. D. Gunn, P. E. Fecci, and D. M. Ashley, “Brain immunology and immunotherapy in brain tumours,” Nat. Rev. Cancer, vol. 20, no. 1, pp. 12–25, 2020.
4. Y. M. A. Mohammed, S. El Garouani, and I. Jellouli, “A survey of methods for brain tumor segmentation-based MRI images,” J. Comput. Des. Eng., vol. 10, no. 1, pp. 266–293, 2023.
5. M. K. Abd-Ellah, A. I. Awad, A. A. M. Khalaf, and H. F. A. Hamed, “A review on brain tumor diagnosis from MRI images: Practical implications, key achievements, and lessons learned,” Magn. Reson. Imaging, vol. 61, pp. 300–318, 2019.
6. W. T. Kimberly et al., “Brain imaging with portable low-field MRI,” Nat. Rev. Bioeng., vol. 1, no. 9, pp. 617–630, 2023.
7. D. Drees, F. Eilers, and X. Jiang, “Hierarchical Random Walker Segmentation for Large Volumetric Biomedical Images,” IEEE Trans. Image Process., vol. 31, pp. 4431–4446, 2022.
8. J. Pruthi, S. Arora, and K. Khanna, “Brain tumor segmentation using river formation dynamics and active contour model in magnetic resonance images,” Neural Comput. Appl., vol. 34, no. 14, pp. 11807–11816, 2022.
9. V. Govindaraj, A. Thiyagarajan, P. Rajasekaran, Y. Zhang, and R. Krishnasamy, “Automated

unsupervised learning-based clustering approach for effective anomaly detection in brain magnetic resonance imaging (MRI)," IET Image Process., vol. 14, no. 14, pp. 3516–3526, 2020.
10. U. Baid et al., "A Novel Approach for Fully Automatic Intra-Tumor Segmentation With 3D U-Net Architecture for Gliomas," Front. Comput. Neurosci., vol. 14, 2020.
11. H. Chen, Z. Qin, Y. Ding, L. Tian, and Z. Qin, "Brain tumor segmentation with deep convolutional symmetric neural network," Neurocomputing, vol. 392, pp. 305–313, Jun. 2020.
12. M. M. Thaha, K. P. M. Kumar, B. S. Murugan, S. Dhanasekeran, P. Vijayakarthick, and A. S. Selvi, "Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images," J. Med. Syst., vol. 43, no. 9, p. 294, 2019.
13. S. Pereira, A. Pinto, V. Alves, and C. A. Silva, "Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images," IEEE Trans. Med. Imaging, vol. 35, no. 5, pp. 1240–1251, 2016.
14. M. Kass, A. Witkin, and D. Terzopoulos, "Snakes: Active contour models," Int. J. Comput. Vis., vol. 1, no. 4, pp. 321–331, 1988.
15. Q. Li, T. Deng, and W. Xie, "Active contours driven by divergence of gradient vector flow," Signal Processing, vol. 120, pp. 185–199, Mar. 2016.
16. L. Dai, J. Ding, and J. Yang, "Inhomogeneity-embedded active contour for natural image segmentation," Pattern Recognit., vol. 48, no. 8, pp. 2513–2529, Aug. 2015.
17. V. Caselles, F. Catté, T. Coll, and F. Dibos, "A geometric model for active contours in image processing," Numer. Math., vol. 66, no. 1, pp. 1–31, 1993.
18. A. Bhandari, J. Koppen, and M. Agzarian, "Convolutional neural networks for brain tumour segmentation," Insights Imaging, vol. 11, no. 1, p. 77, 2020.
19. M. Rasool et al., "A Hybrid Deep Learning Model for Brain Tumour Classification," Entropy, vol. 24, no. 6, 2022.
20. S. Pare, A. Kumar, V. Bajaj, and G. K. Singh, "An efficient method for multilevel color image thresholding using cuckoo search algorithm based on minimum cross entropy," Appl. Soft Comput., vol. 61, pp. 570–592, Dec. 2017.
21. S. Osher and J. A. Sethian, "Fronts propagating with curvature-dependent speed: Algorithms based on Hamilton-Jacobi formulations," J. Comput. Phys., vol. 79, no. 1, pp. 12–49, Nov. 1988.
22. T. F. Chan and L. A. Vese, "Active contours without edges," IEEE Trans. Image Process., vol. 10, no. 2, pp. 266–277, 2001.
23. Z. Jia and D. Chen, "Brain Tumor Identification and Classification of MRI images using deep learning techniques," IEEE Access, p. 1, 2020.
24. P. Oza, P. Sharma, S. Patel, and A. Bruno, "A Bottom-Up Review of Image Analysis Methods for Suspicious Region Detection in Mammograms," J. Imaging, vol. 7, no. 9, 2021.
25. A. Singh and S. Kumar, "A novel dice similarity measure for IFSs and its applications in pattern and face recognition," Expert Syst. Appl., vol. 149, p. 113245, 2020.
26. S. Husham et al., "Comparative analysis between active contour and otsu thresholding segmentation algorithms in segmenting brain tumor magnetic resonance imaging," J. Inf. Technol. Manag., 2021.
27. M. A. Kabir, "Automatic Brain Tumor Detection and Feature Extraction From Mri Image," Sci. World J., 2020.
28. M. Sujan, N. Alam, S. Abdullah, and M. Jahirul, "A Segmentation based Automated System for Brain Tumor Detection," Int. J. Comput. Appl., 2016.
29. S. Iqbal, M. U. Ghani, T. Saba, and A. Rehman, "Brain tumor segmentation in multi-spectral MRI using convolutional neural networks (CNN)," Microsc. Res. Tech., 2018.
30. M. T. Nyo, F. Mebarek-Oudina, S. S. Hlaing, and N. A. Khan, "Otsu's thresholding technique for MRI image brain tumor segmentation," Multimed. Tools Appl., 2022.