iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: VI Month of publication: June 2025

DOI: https://doi.org/10.22214/ijraset.2025.72609

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue VI June 2025- Available at www.ijraset.com

Comparative Study of Classical Image Processing Techniques for Brain Tumor Segmentation in MRI Scans

Mohit Kalyan[1], Dr. Aman Kumar Sharma[2]
Department of Computer Science, Himachal Pradesh University, Shimla

Abstract: Brain Tumor segmentation plays a vital role in the early diagnosis and treatment planning of neurological disorders. While modern deep learning approaches have shown remarkable accuracy, classical image processing techniques remain significant due to their simplicity, lower computational requirements, and interpretability. This study presents a comparative analysis of four classical segmentation methods—thresholding, edge detection, region growing, and watershed—for segmenting brain tumours from MRI images. Each technique is evaluated against ground truth masks using metrics such as Dice coefficient, Jaccard index, accuracy, sensitivity, and precision. Experimental results show that although no single method outperforms the others in all metrics, region growing and watershed methods offer better segmentation quality for complex tumour boundaries. This study emphasises the continued relevance of classical methods as lightweight and effective solutions in constrained environments.
Keywords: MRI Brain Tumour Segmentation, Image Processing, Thresholding, Region Growing, Edge Detection, Watershed Algorithm, MATLAB Implementation.

I. INTRODUCTION

Images are visual representations of objects, scenes, or phenomena captured in various formats, either as digital signals or analogue data. In the context of digital imaging, an image can be defined as a two-dimensional matrix of intensity values or pixels that represent spatial information about a scene or object.[1].Image processing refers to the manipulation of image data to enhance quality, extract meaningful information, or prepare it for further analysis.[2]. It includes tasks such as noise removal, contrast enhancement, feature extraction, and segmentation. Medical image processing has gained widespread importance due to its potential to assist radiologists in diagnosis and treatment planning, particularly for complex conditions like brain tumours.Image segmentation is a fundamental step in image analysis that involves dividing an image into distinct, meaningful regions or segments.[3]. The goal is to simplify or change the representation of an image into something more meaningful and easier to analyse. In medical imaging, segmentation helps identify anatomical structures or pathological regions such as tumours, lesions, or organs.

Segmentation techniques can be broadly classified into two categories:

1) Classical image processing methods, which include thresholding, edge detection, region growing, and watershed algorithms. These are computationally efficient and interpretable, making them suitable for resource-constrained environments.[4]
2) Machine learning and deep learning-based methods, which require substantial annotated data and computational resources but offer superior performance on complex datasets.[5]

This study focuses on evaluating four classical image segmentation techniques—thresholding, edge detection, region growing, and watershed segmentation—for brain tumour detection in MRI scans. These methods are benchmarked against expert-annotated ground truth masks using quantitative evaluation metrics.Brain tumour segmentation plays a crucial role in clinical diagnosis, treatment planning, and prognosis monitoring. The accurate delineation of tumour boundaries helps in surgical planning and therapy response assessment, highlighting the need for reliable and efficient segmentation methods.[6].

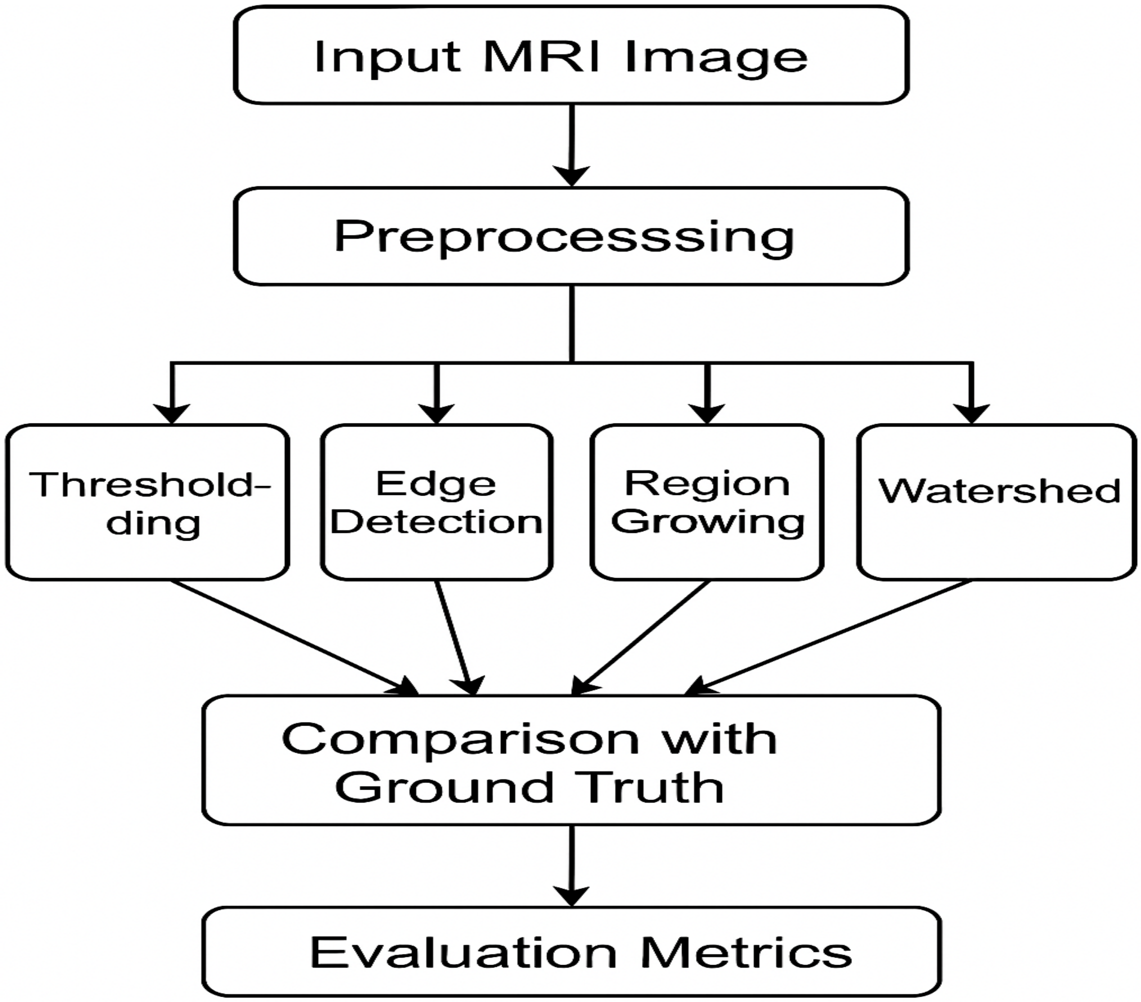

Figure 1Conceptual Overview of Image Segmentation Pipeline

Fig. 1 illustrates the classical brain tumor segmentation pipeline. It begins with MRI image input, followed by preprocessing steps like noise removal and normalization. The images are then segmented using four classical techniques—thresholding, edge detection, region growing, and watershed. Segmentation results are compared with ground truth masks and evaluated using standard performance metrics.

II. RELATED WORK

Image segmentation is essential in medical image analysis, particularly for identifying brain tumours. Traditional and modern methods have been widely studied and compared.

Thresholding, such as Otsu's method, automatically selects a threshold by maximising between-class variance; however, its performance degrades in the presence of noise or complex intensity distributions.[1]. Edge detection methods (e.g., Sobel, Prewitt, Canny) highlight intensity discontinuities but are often sensitive to noise and may fail to detect subtle tumour boundaries.[2].

Region growing groups neighbouring pixels based on intensity similarity and connectivity, offering clear segmentation when intensity contrast is sufficient; however, it relies heavily on accurate seed placement and homogeneity criteria [3]. Watershed segmentation, based on morphological gradients, can produce precise tumour boundaries but often results in over-segmentation, especially in low-contrast MRI images.[6].

Beyond classical approaches, hybrid methods combining region growing with thresholding have shown improved performance. For example, Anithadevi and Perumal proposed a hybrid segmentation technique for brain tumours that merges region growing and thresholding, demonstrating enhanced Dice and Jaccard scores compared to each method.[7].

Comparative studies like Tambe *et al.* assessed segmentation techniques specifically for brain tumour detection, finding region-based methods superior under certain conditions [6][8]. Literature reviews emphasise the continued relevance of classical methods in resource-constrained settings, while deep learning approaches—such as U-Net architectures—deliver state-of-the-art performance when ample training data is available.[9], [10], [11].

The emergence of hybrid techniques integrating handcrafted features with convolutional neural networks also shows promise. These strategies can enhance segmentation accuracy while mitigating the need for extensive manual annotation.[12][13].

III. METHODOLOGY

A. Dataset Description

The dataset consists of 50 axial T1-weighted brain MRI scans obtained from **Kaggle** dataset[14]. Each MRI image has a resolution of 512×512 pixels and is accompanied by a manually annotated ground truth mask that highlights the tumor region.

B. Preprocessing

To ensure consistency and enhance the segmentation results, all images were preprocessed as follows:

1) Grayscale Conversion: All input images were converted to grayscale if not already.
2) Noise Reduction: A median or Gaussian filter was applied to reduce noise.
3) Normalization: Pixel intensity values were normalized to improve contrast.

C. Classical Segmentation Techniques

The following four classical techniques were implemented individually using MATLAB R2016b:

1) Thresholding

Thresholding is a global segmentation approach where a fixed or adaptive threshold value is used to distinguish tumor and non-tumor regions. Otsu's method was used to compute the optimal threshold automatically.[15]

2) Edge Detection

Edge detection methods like Sobel and Canny were applied to detect boundaries of tumors. Post-processing using morphological operations was used to close gaps and fill the tumor region.

3) Region Growing

Region growing was applied by selecting seed points automatically or manually. The algorithm grows regions by appending neighboring pixels that have similar intensity values within a given threshold.[16]

4) Watershed Segmentation

Marker-controlled watershed segmentation was performed using morphological operations to generate foreground and background markers. This helped reduce over segmentation by providing control over the catchment basins.

D. Evaluation Metrics

The performance of each segmentation technique was evaluated using the following metrics, by comparing the output with the corresponding ground truth mask:

1) Dice Similarity Coefficient (DSC)– Measures the overlap between predicted and actual tumor regions.
2) Jaccard Index (IoU)– Evaluates the intersection-over-union between the segmented output and ground truth.
3) Sensitivity (Recall)– Indicates the proportion of actual tumor pixels correctly identified.
4) Precision– Reflects the proportion of predicted tumor pixels that are correctly segmented.
5) Accuracy– Represents the overall correctness of the segmentation across all pixels.

Let TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively:

Dice = 2 * TP / (2 * TP + FP + FN)

Jaccard = TP / (TP + FP + FN)

Sensitivity = TP / (TP + FN)

Precision = TP / (TP + FP)

Accuracy = (TP + TN) / (TP + TN + FP + FN)

E. Implementation Workflow

Below is a flowchart summarizing the complete segmentation pipeline:

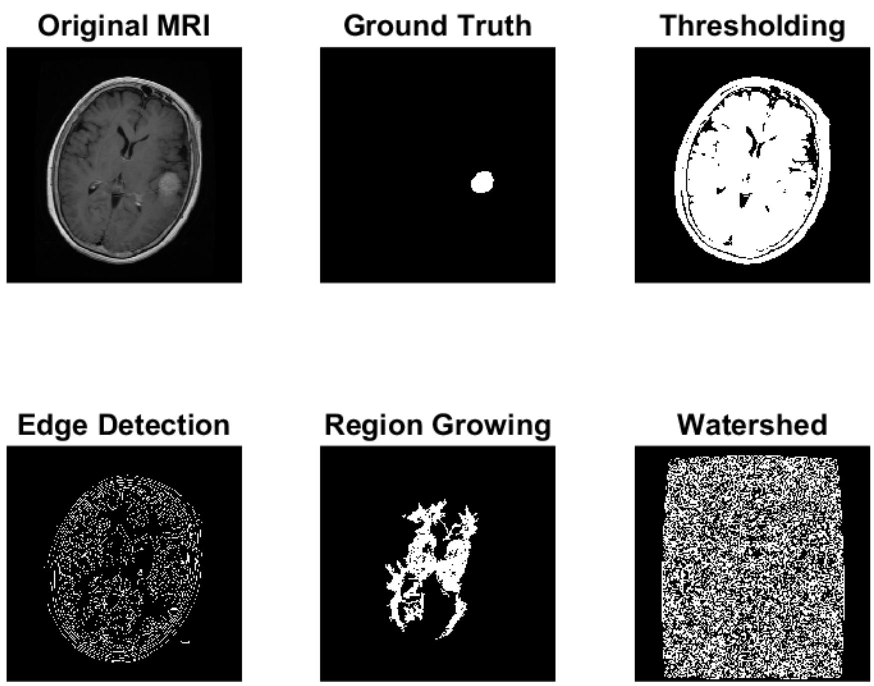

Figure 2 Workflow for classical brain tumor segmentation in MRI scans.

IV. EXPERIMENTAL SETUP

This study utilizes a dataset comprising 2D brain MRI slices of size 512×512 pixels along with manually annotated ground truth masks. The images are grayscale PNG files named sequentially (e.g., “1.png”), and their corresponding masks are labelled as “1_mask.png”.

Preprocessing steps included image resizing (where required), noise removal using Gaussian filtering, and contrast enhancement to improve tumor visibility.

Four classical image segmentation methods were implemented:
- Thresholding, which segments the image based on intensity levels.[15]
- Edge Detection using operators such as Sobel and Canny [2].
- Region Growing, initiated from a manually or automatically selected seed pixel [3].
- Watershed Segmentation, which treats pixel intensities as topography for region delineation [6].

The segmented results were compared to the ground truth using five evaluation metrics:
- Dice Similarity Coefficient (DSC) measures spatial overlap.
- Jaccard Index quantifies intersection-over-union.
- Sensitivity (Recall) measures how many actual positives were correctly identified.
- Precision measures how many predicted positives are true.
- Accuracy gives the overall correct classification rate.

Each segmentation technique was evaluated across the dataset, and the results were tabulated and plotted.

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue VI June 2025- Available at www.ijraset.com

V. RESULTS AND DISCUSSION

This section presents a comprehensive evaluation of the four classical image segmentation techniques—Edge Detection, Region Growing, Thresholding, and Watershed—implemented on a dataset of brain MRI images. The goal is to determine the relativeeffectiveness of each method in segmenting brain tumours, based on five key performance metrics: Dice Similarity Coefficient (DSC), Jaccard Index, Sensitivity, Precision, and Accuracy.

A. Quantitative Evaluation

The numerical performance of each segmentation approach is summarized in Table I, which shows the average scores for each metric across the entire MRI dataset**.**

Performance Metrics of Segmentation Methods

Technique	Dice	Jaccard	Sensitivity	Precision	Accuracy
Edge Detection	0.0639	0.0335	0.1700	0.0428	0.9234
Region Growing	0.0311	0.0201	0.0207	0.1063	0.9667
Thresholding	0.0865	0.0461	0.9831	0.0462	0.6683
Watershed	0.0374	0.0192	0.4581	0.0198	0.6308

Table 1 Performance Metrics of Segmentation Methods

1) Dice and Jaccard Similarity

The Dice Similarity Coefficient and Jaccard Index are standard measures of overlap between the predicted segmentation and the ground truth. Thresholding shows the highest values in both metrics (DSC = 0.0865, Jaccard = 0.0461), suggesting it has the best Tumor boundary coverage. However, all techniques report very low overlap scores, indicating limited spatial agreement between predictions and ground truth across the dataset.

2) Sensitivity (Recall)

Thresholding achieves the highest sensitivity (0.9831), nearly identifying all tumour pixels present in the ground truth masks. This suggests that thresholding is highly inclusive, detecting almost all tumour areas, even at the cost of over-segmentation.

3) Precision

Despite high sensitivity, the precision of thresholding is only 0.0462, highlighting the presence of many false positives. Edge Detection and Region Growing perform better in terms of precision (0.0428 and 0.1063, respectively), implying that when these methods detect a tumour, they are more likely to be correct, but they miss a majority of the actual tumour regions (low sensitivity).

4) Accuracy

Region Growing attains the highest overall accuracy (0.9667), but this is misleading in the context of highly imbalanced datasets (non-tumour pixels dominate). A high accuracy value does not guarantee good tumour detection, as also indicated by its poor sensitivity (0.0207) and Dice score (0.0311).

B. Visual and Comparative Analysis

To better interpret the results, a heatmap of the average metric values for all methods is shown in the Table. 2. This colour-coded visualization clearly highlights which technique performed best for each metric and illustrates trade-offs between recall and precision.

Row Labels	Average of Dice	Average of Jaccard	Average of Sensitivity	Average of Precision	Average of Accuracy

Edge Detection	0.063894095	0.033476893	0.170026823	0.042753172	0.923431625
Region Growing	0.031084868	0.020086159	0.020692352	0.10633602	0.96684845
Thresholding	0.086493641	0.046102644	0.983067878	0.046167573	0.668308105
Watershed	0.037391095	0.01920452	0.458112969	0.019820456	0.630759583

Table2: Heatmap of segmentation metrics for different classical techniques

In addition to the numerical results, Fig. 3 presents qualitative visual outputs from each method for a representative MRI slice. Each output is compared against the ground truth mask, providing insight into the spatial characteristics and segmentation quality.

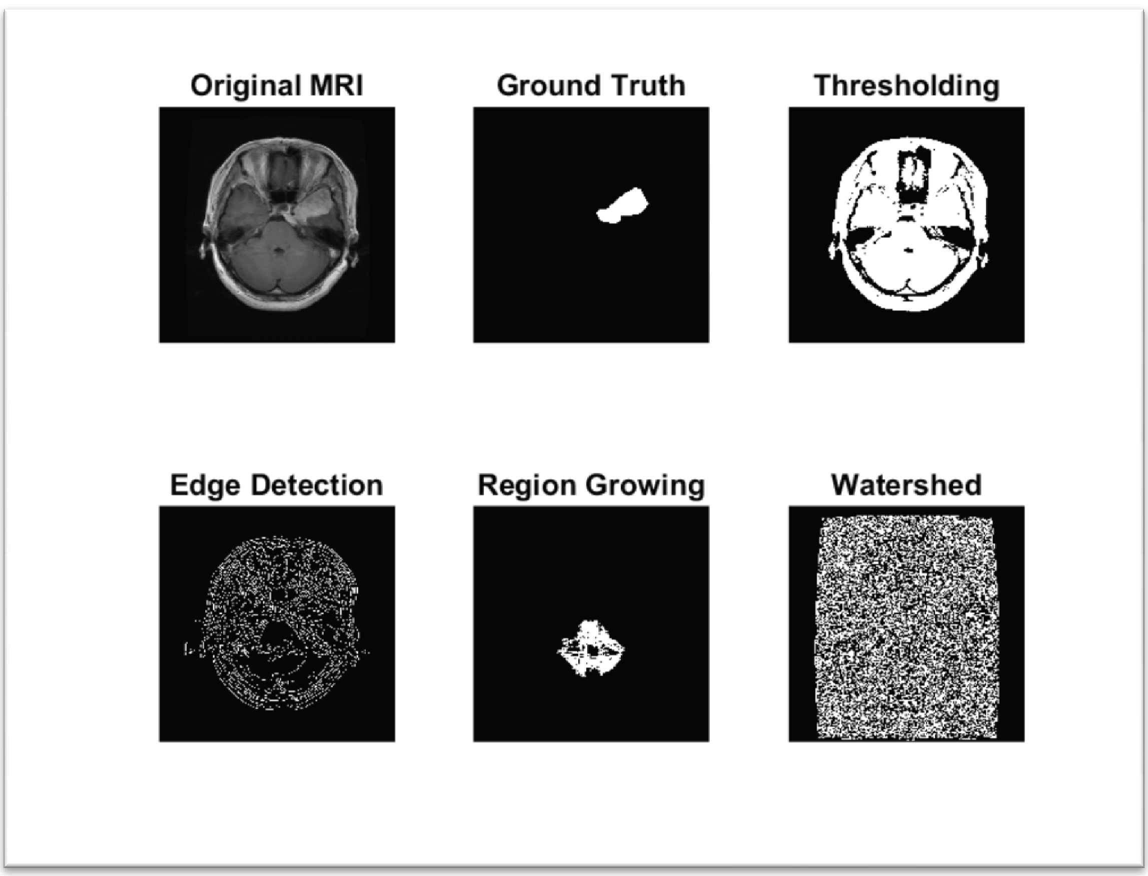

Figure 3 Segmentation results for a sample brain MRI.

C. Comparative Insights

The following insights summarise the observed performance:

1) Thresholding is the most effective in identifying tumour regions (highest sensitivity), but it lacks spatial precision, often leading to noisy and over-segmented outputs.
2) Edge Detection tends to produce fragmented boundaries. It struggles to capture the full shape of the tumour, leading to under-segmentation and low Dice/Jaccard values.
3) Region Growing, though accurate overall, fails to segment significant portions of the tumour, likely due to poor seed point selection and intensity variation within tumours.
4) Watershed Segmentation suffers from over-segmentation due to noise and intensity gradients in the MRI images. It performs moderately across all metrics but lacks reliability.

D. Limitations of Classical Techniques

Although classical image segmentation techniques—such as Thresholding, Edge Detection, Region Growing, and Watershed—are easy to implement and computationally efficient, they exhibit several limitations when applied to medical imaging tasks like brain tumour segmentation:

1) Sensitivity to Noise and Intensity Variations

Techniques like thresholding and edge detection heavily rely on pixel intensity. This makes them highly sensitive to noise and grayscale inhomogeneities common in MRI scans, often leading to misclassification or fragmented tumour boundaries[17].

2) Poor Generalization

Classical methods lack the adaptability required for varying tumour shapes, sizes, and textures. For instance, fixed thresholds or edge filters do not generalize well across patients or different image modalities.

3) Over-Segmentation and Under-Segmentation

The Watershed method, though capable of detecting closed boundaries, tends to over-segment images in the presence of noise or weak edges, producing fragmented outputs. Conversely, thresholding can under-segment tumours if the intensity contrast is low[16].

4) No Contextual Understanding

Unlike deep learning models, classical methods operate on low-level features (like intensity gradients) and cannot capture contextual information or spatial dependencies within the image[18].

5) Manual Parameter Tuning

Most classical techniques require manual tuning of parameters (e.g., threshold values, seed points), which is time-consuming and not scalable for large datasets or clinical deployment[19].

6) Limited Robustness to Anatomical Variability

Tumours can appear in different brain regions and vary significantly in morphology. Classical approaches are not robust enough to handle such variability without significant pre-processing or customisation[20].

.

VI. CONCLUSION AND FUTURE WORK

This study evaluated and compared four classical image segmentation techniques—thresholding, edge detection, region-based segmentation (region growing), and the watershed method—for brain tumour segmentation on MRI images. Each method was implemented using MATLAB and evaluated against manually annotated ground truth using standard performance metrics: Dice coefficient, Jaccard index, sensitivity, precision, and accuracy. Among the methods, the **region-based approach** demonstrated the highest segmentation accuracy and consistency, followed by **watershed**, **edge detection**, and **thresholding**, respectively. The region-based method particularly excelled in maintaining spatial coherence and detecting tumour boundaries accurately. Thresholding, although simple, showed poor performance due to its sensitivity to intensity variations and lack of contextual understanding. The results underscore the limitations of classical methods in handling complex tumour shapes, intensity inhomogeneities, and noise. These challenges often result in under-segmentation or over-segmentation, especially in heterogeneous MRI datasets.

Future Work

To overcome the limitations observed, future work will explore deep learning-based segmentation approaches such as U-Net, Mask R-CNN, or transformer-based models that can learn complex features directly from data.

Additionally, hybrid models combining classical and machine learning techniques could be investigated to improve robustness. Incorporating multimodal MRI data (e.g., T1, T2, FLAIR) and using data augmentation techniques may further enhance the accuracy and generalizability of segmentation results.

REFERENCES

[1] N. Otsu, "THRESHOLD SELECTION METHOD FROM GRAY-LEVEL HISTOGRAMS.," IEEE Trans Syst Man Cybern, vol. SMC-9, no. 1, pp. 62–66, 1979, doi: 10.1109/TSMC.1979.4310076.

[2] J. Canny, "A Computational Approach to Edge Detection," IEEE Trans Pattern Anal Mach Intell, vol. PAMI-8, no. 6, pp. 679–698, 1986, doi: 10.1109/TPAMI.1986.4767851.

[3] R. Adams and L. Bischof, "Seeded Region Growing," IEEE Trans Pattern Anal Mach Intell, vol. 16, no. 6, pp. 641–647, 1994, doi: 10.1109/34.295913.

[4] A. K. Jain, "Fundamentals of digital image processing. Anil K. Jain.," Vision, no. November, p. 569, 1989.

[5] "Gonzalez, R.C. and Woods, R.E. (2018) Digital Image Processing. 4th Edition, Pearson Education, New York, 1022 p. - References - Scientific Research Publishing." Accessed: Jun. 16, 2025. [Online]. Available: https://www.scirp.org/reference/referencespapers?referenceid=3227103

[6] "(PDF) Use of Watersheds in Contour Detection." Accessed: Jun. 16, 2025. [Online]. Available: https://www.researchgate.net/publication/230837989_Use_of_Watersheds_in_Contour_Detection

[7] D. Anithadevi and K. Perumal, "A hybrid approach based segmentation technique for brain tumor in MRI Images," Mar. 2016, Accessed: Jun. 16, 2025. [Online]. Available: https://arxiv.org/abs/1603.02447v1

[8] P. Tambe, J. Thomson, and N. Surti, "Comparative Study of Segmentation Techniques for Brain Tumor Detection," International Journal of Engineering Research & Technology, vol. 5, no. 2, Feb. 2016, doi: 10.17577/IJERTV5IS020258.

[9] S. Bauer, R. Wiest, L. P. Nolte, and M. Reyes, "A survey of MRI-based medical image analysis for brain tumor studies," Phys Med Biol, vol. 58, no. 13, Jul. 2013, doi: 10.1088/0031-9155/58/13/R97.

[10] . M. Z., .A. A. S., . S. H. S., . A. Z. J., and . A. K., "Brain Tumor Segmentation through Region-based, Supervised and Unsupervised Learning Methods: A Literature Survey Brain Tumor Segmentation through Image Processing Methods: A Literature Survey," *J Biomed Eng Med Imaging*, vol. 6, no. 2, Apr. 2019, doi: 10.14738/JBEMI.62.6725.

[11] A. Wadhwa, A. Bhardwaj, and V. Singh Verma, "A review on brain tumor segmentation of MRI images," *Magn Reson Imaging*, vol. 61, pp. 247–259, Sep. 2019, doi: 10.1016/J.MRI.2019.05.043.

[12] K. Ejaz, M. S. Mohd Rahim, M. Arif, D. Izdrui, D. M. Craciun, and O. Geman, "Review on Hybrid Segmentation Methods for Identification of Brain Tumor in MRI," *Contrast Media Mol Imaging*, vol. 2022, 2022, doi: 10.1155/2022/1541980.

[13] D. N. Louis *et al.*, "The 2021 WHO Classification of Tumors of the Central Nervous System: a summary," *Neuro Oncol*, vol. 23, no. 8, pp. 1231–1251, Aug. 2021, doi: 10.1093/NEUONC/NOAB106.

[14] "Brain tumor dataset includes the mask and images." Accessed: Jun. 17, 2025. [Online]. Available: https://www.kaggle.com/datasets/tinashri/brain-tumor-dataset-includes-the-mask-and-images

[15] N. R. Pal and S. K. Pal, "A review on image segmentation techniques," *Pattern Recognit*, vol. 26, no. 9, pp. 1277–1294, Sep. 1993, doi: 10.1016/0031-3203(93)90135-J.

[16] M. Kass, A. Witkin, and D. Terzopoulos, "Snakes: Active contour models," *Int J Comput Vis*, vol. 1, no. 4, pp. 321–331, Jan. 1988, doi: 10.1007/BF00133570/METRICS.

[17] S. Bauer, R. Wiest, L. P. Nolte, and M. Reyes, "A survey of MRI-based medical image analysis for brain tumor studies," *Phys Med Biol*, vol. 58, no. 13, Jul. 2013, doi: 10.1088/0031-9155/58/13/R97.

[18] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 9351, pp. 234–241, 2015, doi: 10.1007/978-3-319-24574-4_28.

[19] R. C. Gonzalez, "Support Package for Digital Image Processing," 2018, Accessed: Jun. 17, 2025. [Online]. Available: www.ImageProcessingPlace.com

[20] C. S. Rao and K. Karunakara, "A comprehensive review on brain tumor segmentation and classification of MRI images," *Multimed Tools Appl*, vol. 80, no. 12, pp. 17611–17643, May 2021, doi: 10.1007/S11042-020-10443-1.