



ENHANCED BRAIN TUMOR DETECTION USING AI-BASED MULTIMODAL MRI ANALYSIS AND HYBRID SEGMENTATION TECHNIQUES

¹Uttam, ²Sowmya, ³Sarvesh Mohan Gaonkar ⁴Harsharaj S Shetty, ⁵Rahul K

¹Final year B.E. Student, ² Assistant Professor, ISE, ³Final year B.E. Student, ⁴Final year B.E. Student, ⁵Final year B.E. Student

¹Department of Information Science & Engineering,
¹Srinivas Institute of Technology, Mangaluru, India.

Abstract: Brain tumor detection is a critical task in medical imaging, where timely and precise diagnosis can greatly enhance patient outcomes. This paper presents an AI-based framework for enhanced identification of brain cancers using multimodal MRI scans. The proposed system integrates advanced architectures for deep learning using traditional images processing techniques to take use of both data-driven and traditional segmentation approaches. Using T1, T1-Gd, T2, and FLAIR sequences, the framework applies pre-processing, optimized multi-level thresholding via Harmony Search Optimization, and morphological operations to extract tumor regions effectively. Furthermore, deep neural networks such as InceptionResNetV2 and DenseNet121 are evaluated for classification tasks, aided by transfer learning and data augmentation. Comparative analysis with standard convolutional networks demonstrates the superiority of the hybrid model in terms of accuracy, Dice coefficient, and execution efficiency. The results validate the potential of combining AI and hybrid segmentation techniques for reliable and scalable brain tumor detection.

Keywords: Brain Tumor Detection, MRI, Deep Learning, Hybrid Segmentation, Transfer Learning

I. INTRODUCTION

In order to improve patient outcomes, lower treatment costs, and improve quality of life, early diagnosis of brain tumors is essential. Magnetic resonance imaging (MRI) is the most widely used non-invasive imaging technique for brain tumor diagnosis, which may give precise structural details about soft tissues. However, radiologists' interpretation of MRI scans is heavily reliant on their experience, which can result in inconsistent results and delays in diagnosis. The need for intelligent and automated technologies that can help clinicians correctly identify tumors is developing as the number of brain tumors worldwide rises and as the amount of medical imaging data increases.

Deep learning, a subset of artificial intelligence (AI), has become a transformative approach in medical imaging. By learning complex patterns from annotated datasets, AI models can provide reliable diagnostic support, segment tumor regions, and classify tumor types. Conventional techniques for picture segmentation, like thresholding and clustering, are computationally efficient but often lack precision when dealing with heterogeneous tumor structures. Convolutional neural networks (CNNs), however offer superior accuracy but demand extensive training data and computational resources.

Hybrid methods that blend deep learning models with traditional image processing techniques have shown a lot of potential in brain tumor detection tasks. These systems harness the strengths of both methodologies—employing traditional techniques for efficient preprocessing and noise reduction, while utilizing AI for accurate classification and segmentation. The proposed method integrates multi-level thresholding with Harmony Search Optimization for precise tumor segmentation, followed by categorization with deep learning models that have already been trained fine-tuned via transfer learning. By evaluating the performance of multiple architectures and techniques, the study aims to develop a robust and scalable solution suitable for clinical deployment.

II. RESEARCH METHODOLOGY

The methodology outlines the systematic approach adopted for the development, training, and evaluation of an AI-based method for detecting brain tumors using MRI scans. It includes the study's dataset, data sources, preprocessing techniques, feature extraction, classification methods, and performance evaluation metrics. The following subsections provide a comprehensive description.

2.1 Population and Sample

The study focuses on MRI scans used in the detection of brain tumors, specifically targeting three tumor types: glioma, meningioma, and pituitary tumors. The population comprises publicly available and expert-annotated MRI datasets including the BraTS 2017, BraTS 2021, and Figshare Brain Tumor Dataset. These datasets offer a wide representation of different tumor types and imaging modalities such as T1, T1-Gd (contrast-enhanced), T2, and FLAIR. A sum of 3000+ MRI slices were selected as the sample for training and evaluation, ensuring diversity in tumor size, location, and intensity distribution.

2.2 Data and Sources of Data

Anonymized MRI images from reliable internet medical imaging repositories were used as secondary data in this investigation. The BraTS datasets provided multimodal brain MRIs with corresponding tumor segmentation masks. The Figshare dataset contributed labeled images classified into glioma, meningioma, and pituitary tumors. Preprocessing was done on the dataset to eliminate non-brain tissues (skull stripping), standardized to isotropic resolution, and transformed from 3D to 2D slices using tools like ImageJ for computational efficiency.

2.3 Theoretical Framework

The model comprises both segmentation and classification components. The segmentation process involves traditional thresholding enhanced by optimization, while the classification is handled using deep learning networks.

- **Dependent Variable:** Presence and type of brain tumor (glioma, meningioma, pituitary, or no tumor).
- **Independent Variables:** Pixel intensities, histogram-derived features, and deep features from convolutional layers.

Segmentation is carried out using a Harmony Search Optimization (HSO)-based multi-level thresholding technique, which dynamically adjusts to the pixel intensity distributions of MRI images. This method identifies optimal threshold values by maximizing objective functions like Otsu's variance or Kapur's entropy, allowing for precise separation of tumor tissue from surrounding brain structures. To improve the quality of the segmented output, morphological operations such as erosion and dilation are applied to reduce noise and enhance tumor boundaries. Finally, connected component analysis is used to isolate the most relevant tumor region, filtering out small, non-tumor artifacts.

For classification, deep learning models like InceptionResNetV2, DenseNet121, and Xception are fine-tuned using transfer learning to adapt to medical image features. The use of multiple modalities and hybrid segmentation enhances robustness and generalization across cases.

2.4 Tools and Frameworks

2.4.1 Image Preprocessing and Segmentation

Preprocessing includes:

- Resizing images to a standard resolution.
- Normalizing pixel intensities.
- Skull-stripping and slice selection (central brain regions).

The segmentation employs Otsu's and Kapur's entropy functions as objective functions for multi-threshold selection within the HSO algorithm. This results in segmented images where tumor regions are color-coded and isolated from surrounding tissue.

2.4.2 Feature Extraction and Classification

From the segmented images:

- To extract deep characteristics, one uses CNNs (via TensorFlow/Keras frameworks).
- Transfer learning allows leveraging pre-trained models on ImageNet, retrained on tumor datasets.
- Data augmentation (rotation, flipping, zooming) increases data diversity and model generalization.

Each model is trained with the following parameters:

- Optimizer: Adam
- Loss Function: Categorical Cross-Entropy
- Epochs: 50
- Batch Size: 4
- Validation Strategy: 10-fold cross-validation

2.4.3 Evaluation Metrics

The models are evaluated using:

- Accuracy: Proportion of correctly classified samples.
- Sensitivity (Recall): Ability to detect actual tumor cases.
- Specificity: Ability to correctly identify non-tumor images.
- Dice Coefficient & Jaccard Index: Overlap-based measures between predicted tumor regions and ground truth masks.
- Precision & F1 Score: To assess equilibrium between specificity and sensitivity.

2.5 Model Comparison and Analysis

To validate the efficiency of hybrid segmentation and CNN-based classification, we conducted comparative analysis:

- **Classical vs. Deep Learning segmentation performance:** Classical methods like thresholding and region-growing struggle with complex images, whereas CNN-based segmentation excels at detecting complex characteristics and patterns, improving robustness and accuracy.
- **Inference time and model complexity comparison across CNNs:** Simpler CNNs like LeNet-5 offer faster inference but lower accuracy, while deeper models such as ResNet and DenseNet are computationally costly but more accurate. Hybrid models that combine HSO-based segmentation with pre-trained CNNs balance the trade-off by focusing the CNNs on smaller, relevant regions.

- **Modal performance using different MRI sequences (T1, T1-Gd, FLAIR):** T1-weighted images offer good anatomical detail, T1-Gd images (with gadolinium contrast) enhance tumor visibility, and FLAIR images are useful for detecting lesions near fluid-filled regions. The hybrid approach performed best with T1-Gd images due to their superior tumor contrast.

The study highlights that integrating HSO-based segmentation with pre-trained CNN classifiers results in improved detection accuracy with reduced computational overhead.

III. RESULTS AND DISCUSSION

3.1 Model Performance and Descriptive Results

Several deep learning architectures were used to test the suggested system, and MRI datasets, as outlined in the experimental setup. Performance was assessed on metrics including accuracy, F1-score, sensitivity, specificity, and precision.

For the majority of tasks, the InceptionResNetV2 model performed the best:

- Accuracy: up to 97.22%
- F1-score: 95.39%
- Precision: 97.67%
- Sensitivity: 96.17%

Among tumor classes, pituitary tumors had the highest classification accuracy (97.22%), followed by glioma (93.94%) and meningioma (92.14%).

For detection tasks using the MRI-D dataset, incorporating transfer learning and data augmentation improved model accuracy by approximately 6%, with DenseNet121 and VGG19 also performing well under this configuration:

- Detection Accuracy (with T&D): up to 92.16%
- F1-score: up to 93.75%

When comparing performance across MRI modalities (T1, T1-Gd, and FLAIR), the FLAIR sequence yielded the most reliable results across networks, particularly for tumor detection using InceptionResNetV2, which achieved:

- F1-score (FLAIR): 93.45%
- Accuracy (FLAIR): 91.36%

The proposed Cross-Transformer model, introduced in the second paper, showed competitive detection accuracy while cutting down on training time by a substantial amount requiring nearly five times less computation time compared to InceptionResNetV2, making it a strong candidate for efficient deployment.

Overall, the results confirm that combining classical segmentation techniques with modern deep learning and optimization strategies enhances tumor localization and classification accuracy while improving computational efficiency.

Figures and Tables

Figure 1 illustrates the general system architecture for the proposed brain tumor detection framework, demonstrating the sequential flow from input MRI data to tumor classification through segmentation and CNN-based analysis.

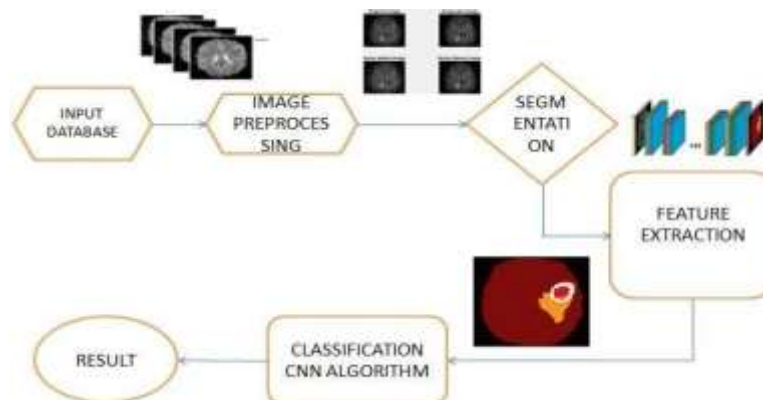


Fig 1: General System Architecture.

Figure 2 shows a collection of T2-weighted normal brain MR images using the multi-level thresholding segmentation approach.

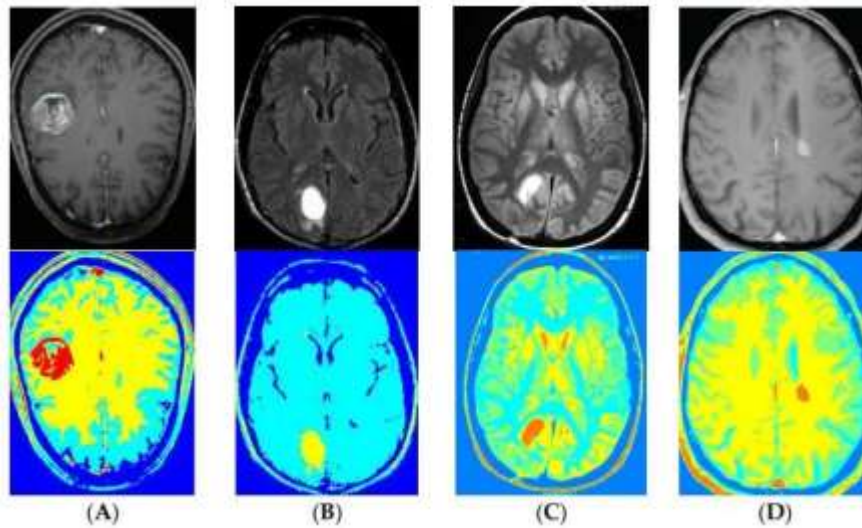


Fig 2: Color segmentation results using multi-level thresholding on T2-weighted images.

Figure 3 illustrates a color-segmented image (Figure 3C) produced by the Harmony Search Optimization (HSO) thresholding technique. The original image is segmented into three layers, each of which is represented by a different color: the backdrop is dark blue, the brain tissue is sky blue, the area around the tumor is yellow, and the tumor core is red.

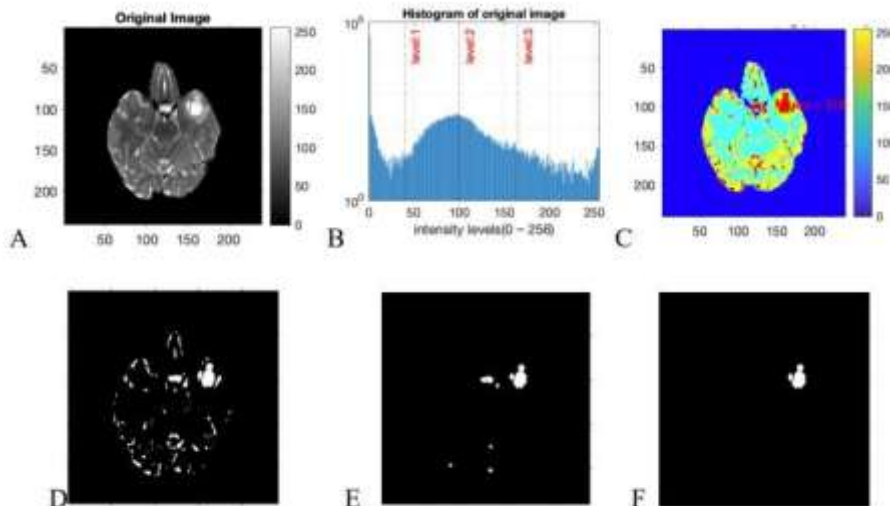


Fig 3. (A) Original MRI scan; (B) corresponding histogram with selected threshold levels; (C) color-segmented image; (D) red-colored tumor core from (C); (E) outcome of morphological processing; (F) final result after connected component analysis.

Conclusion

The suggested AI-based technique for brain tumor detection using MRI scans demonstrates a reliable and effective way to identify and categorize brain cancers early. By integrating traditional methods of image processing, including multi-level thresholding with Harmony Search Optimization, and advanced deep learning models using transfer learning, the system effectively combines accuracy with computational efficiency. The experimental results, drawn from benchmark datasets and multiple MRI modalities, confirm the robustness of the approach in both segmentation and classification tasks. Notably, models like InceptionResNetV2 and DenseNet121, when fine-tuned with domain-specific data, showed high sensitivity and specificity, indicating their potential to assist radiologists in real-world clinical environments.

Despite the promising results, certain challenges remain. The variability in tumor shape, size, and location across patients necessitates the development of more adaptive learning models capable of generalizing across a variety of datasets. Moreover, while multimodal MRI improves detection accuracy, it also introduces complexity in data acquisition and model training. Future work can explore the integration of attention mechanisms and transformer-based architectures to further enhance contextual understanding within MRI slices. Additionally, clinical validation and collaboration with healthcare institutions will be crucial for translating this technology into practical diagnostic tools. Overall, this research affirms AI's revolutionary role in medical imaging and underscores its potential to support timely and accurate brain tumor diagnosis.

REFERENCES

- [1] Aleid, Adham, et al. "Artificial intelligence approach for early detection of brain tumors using MRI images." *Applied Sciences* 13.6 (2023): 3808.
- [2] Anaya-Isaza, Andrés, et al. "Optimizing MRI-based brain tumor classification and detection using AI: A comparative analysis of neural networks, transfer learning, data augmentation, and the cross-transformer network." *European Journal of Radiology*

Open 10 (2023): 100484.

- [3] Bhattacharyya, S.; Maulik, U.; Dutta, P. Multilevel image segmentation with adaptive image context based thresholding. *Appl. Soft Comput.* 2011, 11, 946–962.
- [4] Małyszko, D.; Stepaniuk, J. Adaptive multilevel rough entropy evolutionary thresholding. *Inf. Sci.* 2010, 180, 1138–1158.
- [5] Li, L.; Sun, L.; Xue, Y.; Li, S.; Huang, X.; Mansour, R.F. Fuzzy Multilevel Image Thresholding Based on Improved Coyote Optimization Algorithm. *IEEE Access* 2021, 9, 33595–33607.
- [6] Esparza, E.R.; Calzada, L.A.Z.; Oliva, D.; Heidari, A.A.; Zaldivar, D.; Cisneros, M.P.; Foong, L.K. An efficient harris hawks-inspired image segmentation method. *Expert Syst. Appl.* 2020, 155, 113428.
- [7] Houssein, E.H.; Emam, M.M.; Ali, A.A. An efficient multilevel thresholding segmentation method for thermography breast cancer imaging based on improved chimp optimization algorithm. *Expert Syst. Appl.* 2021, 185, 115651.
- [8] Otsu, N. A threshold selection method from gray-level histograms. *IEEE Trans. Syst. Man Cybern.* 1979, 9, 62–66.
- [9] Kapur, J.N.; Sahoo, P.K.; Wong, A.K.C. A new method for gray-level picture thresholding using the entropy of the histogram. *Comput. Vis. Graph. Image Process.* 1985, 29, 273–285.
- [10] Kabade, R.S.; Gaikwad, M.S. MRI segmentation of brain to detect brain tumor and its area calculation using K-means clustering and fuzzy c-means algorithm. *Int. J. Comput. Sci. Eng. Technol.* 2013, 4, 524–531.

