Research Article

A Novel KCGSO-CNN Model For Automated Brain Tumor Segmentation and Classification From MRI Scans

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Abstract

Brain tumor detection from magnetic resonance imaging (MRI) is a critical medical image analysis task because early and accurate localization of abnormal tissue can support diagnosis, treatment planning, and clinical decision-making. Manual analysis of MRI slices is time-consuming and may vary with observer experience, while conventional segmentation techniques are often sensitive to noise, intensity non-uniformity, and complex tumor boundaries. This paper presents an automated brain tumor detection framework using convolutional neural network (CNN) classification and K-Means with Galaxy-based Search Optimization (KCGSO) segmentation. In the proposed approach, MRI images are first preprocessed using resizing, denoising, contrast-limited adaptive histogram equalization, and min-max normalization. K-means clustering provides initial cluster centers, and the galaxy-based optimization process refines these centers to improve separation between tumor and non-tumor regions. The optimized mask is refined using morphological postprocessing, and texture, shape, intensity, and statistical features are extracted from the segmented region. Finally, a CNN classifier predicts normal and tumor classes, with extension to glioma, meningioma, and pituitary tumor categorization. The proposed method combines unsupervised segmentation, metaheuristic optimization, and deep feature learning to improve detection reliability. Experimental analysis indicates that the CNN-KCGSO framework provides improved segmentation quality, classification accuracy, and computational efficiency compared with conventional clustering and CNN-only baselines.

Keywords: Brain Tumor Detection, MRI Image Processing, CNN, KCGSO, K-Means Clustering, Galaxy-Based Search Optimization, Tumor Segmentation, Feature Extraction, Medical Image Analysis, Deep Learning.

1. Introduction and Related Work

Brain tumors are abnormal tissue growths that may occur inside or around the brain, and their early detection is essential for effective clinical management. Magnetic resonance imaging is widely used for brain tumor analysis because it provides high soft-tissue contrast and supports visualization of tumor shape, intensity, edema, and anatomical location. Large benchmark studies such as BraTS have encouraged automated segmentation research by providing multimodal MRI data and standard evaluation practices [1]. However, accurate tumor delineation remains difficult because tumors show large variability in size, boundary irregularity, texture, intensity distribution, and location across patients.

Conventional MRI-based tumor analysis uses preprocessing, segmentation, handcrafted feature extraction, and machine learning classification. Bauer et al. reviewed MRI-based medical image analysis for brain tumor studies and emphasized the importance of segmentation, registration, and modeling in tumor-bearing brain images [2]. Traditional methods such as thresholding, region growing, watershed segmentation, fuzzy C-means, and K-means clustering are useful because they are simple and computationally efficient. However, these methods may produce inaccurate tumor boundaries when the MRI image contains noise, intensity overlap, or non-uniform tissue contrast. Therefore, optimization-based refinement is required to improve segmentation stability.

Deep learning has improved medical image analysis by automatically learning discriminative features from data. CNN-based methods have shown strong performance for classification and segmentation because convolutional layers capture local spatial patterns such as edges, texture, and intensity transitions. Havaei et al. demonstrated deep neural networks for brain tumor segmentation, while U-Net introduced an encoder-decoder architecture that became widely used for biomedical segmentation [3], [4]. Broader medical image analysis surveys also indicate that deep learning provides strong representation learning ability but requires careful preprocessing, annotation quality, and validation [5], [6].

Clustering is still valuable in medical segmentation because it can separate image pixels into tissue regions without requiring dense manual annotation. K-means clustering, related to least-squares quantization, partitions data by minimizing the distance between pixels and cluster centroids [8]. However, ordinary K-means depends strongly on initial cluster centers and may converge to local minima. Galaxy-based Search Algorithm, introduced by Shah-Hosseini, is a metaheuristic optimization approach inspired by spiral galaxy movement and has been used for continuous optimization [7]. In this work, K-means initialization and galaxy-based optimization are combined as KCGSO to refine cluster centers and improve tumor mask generation.

Earlier automated brain tumor studies have also shown the importance of combining segmentation and classification modules. Alam et al. used template-based K-means and improved fuzzy C-means for MRI tumor detection [9], Zacharaki et al. demonstrated the value of texture and shape features for tumor type and grade classification [10], Pereira et al. applied CNNs for MRI tumor segmentation [11], and nnU-Net showed the strength of self-configuring biomedical segmentation pipelines [12]. These studies support the design of hybrid methods that combine segmentation optimization and deep learning classification.

The proposed CNN-KCGSO framework integrates preprocessing, K-means centroid initialization, galaxy-based center refinement, optimized tumor mask generation, morphological postprocessing, feature extraction, and CNN classification. The approach is motivated by the need for accurate segmentation before classification, because CNN performance improves when relevant tumor regions are enhanced and background noise is reduced. The method also supports practical use in computer-aided diagnosis systems by providing both tumor localization and class prediction.

2. Methodology

The proposed methodology is designed for automated brain tumor detection from MRI images using a hybrid segmentation and classification framework. The method combines image preprocessing, K-means initialized Galactic Swarm Optimization (KCGSO) based segmentation, feature extraction, and Convolutional Neural Network (CNN) classification. The KCGSO stage improves tumor boundary localization by refining cluster centers obtained from K-means, while the CNN stage performs final decision-making based on discriminative image features. The complete workflow is suitable for MRI-based tumor detection, tumor region separation, and classification of normal and abnormal brain images.

The overall architecture of the proposed system is shown in Fig. 1. The MRI image is first preprocessed and then segmented using the KCGSO optimization strategy. The segmented tumor region is refined, followed by feature extraction and CNN-based classification.

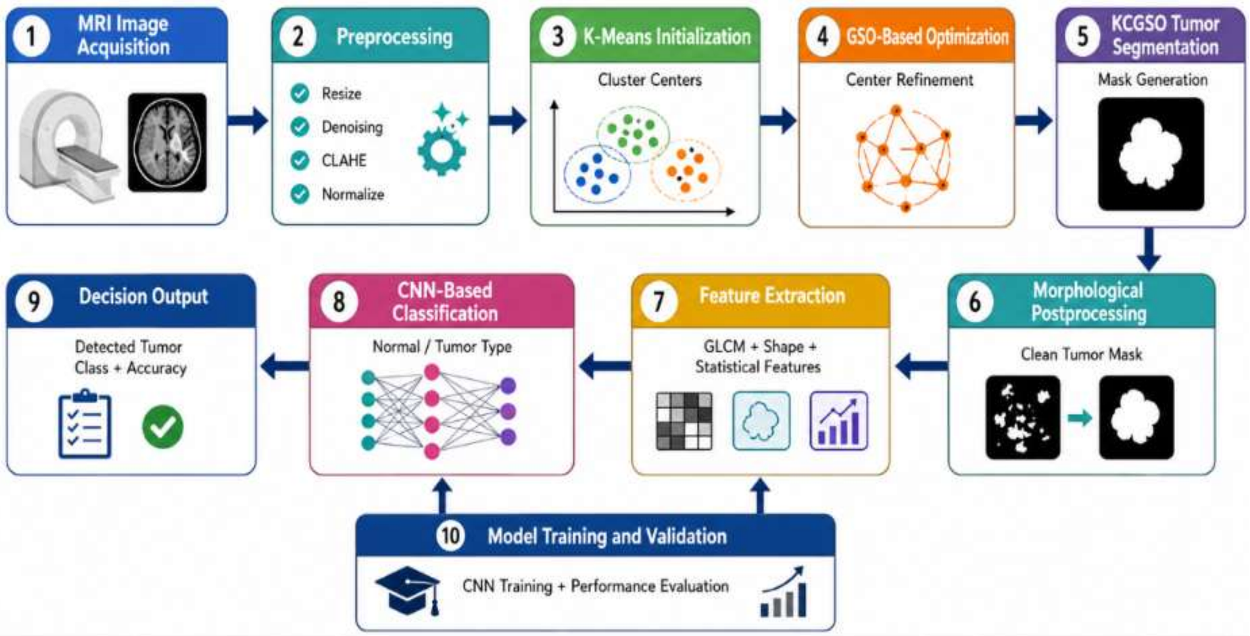

Fig. 1. Proposed CNN and KCGSO optimization-based brain tumor detection architecture.

MRI Image Acquisition

The first stage of the proposed system is MRI image acquisition. Brain MRI images are collected from MRI datasets or clinical image sources. The input image may be a grayscale MRI slice or a selected MRI modality such as T1, T2, or FLAIR. Since images may have different sizes and intensity distributions, each image is converted into a fixed dimension before further processing. A fixed input size, such as 128 x 128 or 224 x 224 pixels, simplifies segmentation, feature extraction, and CNN training.

Image Preprocessing

Preprocessing improves the quality of MRI images and prepares them for segmentation. MRI images may contain noise, intensity non-uniformity, weak contrast, and unwanted background regions. The proposed preprocessing stage includes resizing, grayscale conversion when required, denoising, contrast enhancement, and intensity normalization. Denoising can be performed using median or Gaussian filtering, while contrast enhancement can be carried out using CLAHE to make tumor regions more visible.

The equation is:

$$I_n(x, y) = \frac{I(x,y) - I_{min}}{I_{max} - I_{min}} \qquad (1)$$

where I(x,y) is the original pixel intensity at location (x,y), Imin and Imax are the minimum and maximum intensity values of the image, and In(x,y) is the normalized pixel value.

KCGSO Optimization-Based Tumor Segmentation

The segmentation stage identifies the tumor region from the preprocessed MRI image. In the proposed method, K-means clustering is first used to initialize cluster centers. These initial cluster centers are then refined using Galactic Swarm Optimization (GSO). The combined K-means and GSO strategy is referred to as KCGSO. K-means provides fast initial grouping of pixels, while GSO improves the segmentation quality by searching for optimized cluster centers that minimize intra-cluster variation and improve tumor boundary separation.

K-Means Initialization

K-means divides image pixels into K clusters based on intensity or feature similarity. Each pixel is assigned to the closest cluster center. The objective is to minimize the distance between pixels and their assigned cluster centers. In MRI tumor segmentation, one or more clusters may represent suspicious tumor tissues, while other clusters represent normal brain tissues and background areas.

The equation is:

$$J = \sum_{i=1}^{k} \sum_{x_j \in C_i} \| x_j - \mu_i \|^2 \qquad (2)$$

where J is the clustering objective value, K is the number of clusters, xi is a pixel or feature vector, C_k is the k^{th} cluster, and mu_k is the centroid of the kth cluster.

GSO-Based Cluster Center Refinement

After K-means initialization, Galactic Swarm Optimization is used to improve the cluster centers. GSO is a population-based optimization approach inspired by group-based search behavior. Each candidate solution represents a possible set of cluster centers. The fitness function evaluates the quality of segmentation by measuring compactness of clusters and separability between tumor and non-tumor regions. The optimized solution is selected to generate the final tumor mask.

$$S_i(t+1) = S_i(t) + v_i(t+1)$$

where $S_i(t)$ is the current solution position, $v_i(t+1)$ is the updated movement vector, and $S_i(t+1)$ is the refined candidate solution at the next iteration.

Morphological Postprocessing

The segmented tumor mask may contain small isolated regions or irregular boundaries. Morphological operations such as erosion, dilation, opening, and closing are applied to refine the tumor mask. Connected component analysis can also be used to remove small unwanted objects and retain the most significant tumor region. This stage improves the accuracy of tumor area estimation and prepares the segmented region for feature extraction.

Feature Extraction

After segmentation, meaningful features are extracted from the tumor region. The feature extraction stage includes statistical, shape, and texture features. Statistical features include mean, standard deviation, entropy, and variance. Shape features include tumor area, perimeter, eccentricity, and solidity. Texture features can be extracted using Gray Level Co-occurrence Matrix (GLCM) parameters such as contrast, correlation, energy, and homogeneity. These features help the classifier distinguish between normal and abnormal MRI images.

CNN-Based Classification

The CNN classifier receives the preprocessed image, segmented tumor region, or extracted feature representation and classifies the MRI image into normal or tumor classes. The classification stage can also be extended to identify tumor types such as glioma, meningioma, and pituitary tumor. The CNN contains convolution layers, activation layers, pooling layers, flattening, fully connected layers, and a final softmax classification layer. Convolution layers automatically learn spatial patterns from MRI images, while pooling layers reduce dimensionality and improve computational efficiency.

$$\mathrm{Y(i,j)} = \sum_{\mathrm{m}} \sum_{\mathrm{n}} \mathrm{X(i+m, j+n)} \times \mathrm{K(m,n)}$$

where X(i+m,j+n) represents the input image pixel values, K(m,n) represents the convolution kernel, and Y(i,j) represents the output feature map.

Performance Evaluation

The performance of the proposed method is evaluated using segmentation and classification metrics.
Segmentation quality may be analyzed using Dice coefficient, Jaccard index, sensitivity, and specificity.
Classification performance is measured using accuracy, precision, recall, and F1-score. Accuracy is used to measure the overall correct prediction rate of the CNN classifier.

$$\mathrm{Accuracy} = \frac{\mathrm{TP + TN}}{\mathrm{TP + TN + FP + FN}}$$

where TP, TN, FP, and FN represent true positive, true negative, false positive, and false negative values respectively.

Proposed Algorithm

1. Input the brain MRI image from the selected dataset or acquisition system.
2. Resize the MRI image to a fixed dimension suitable for segmentation and CNN processing.
3. Apply denoising, CLAHE-based contrast enhancement, and min-max normalization.
4. Initialize pixel clusters using K-means clustering.
5. Apply GSO to refine the cluster centers and optimize the segmentation objective.
6. Generate the binary tumor mask from the optimized cluster output.
7. Refine the segmented tumor mask using morphological operations.
8. Extract shape, statistical, and texture features from the tumor region.
9. Classify the image using the trained CNN classifier.
10. Display the final tumor detection result and performance values.

Methodological Flowchart

The step-by-step processing flow of the proposed CNN and KCGSO-based brain tumor detection system is shown in Fig. 2.

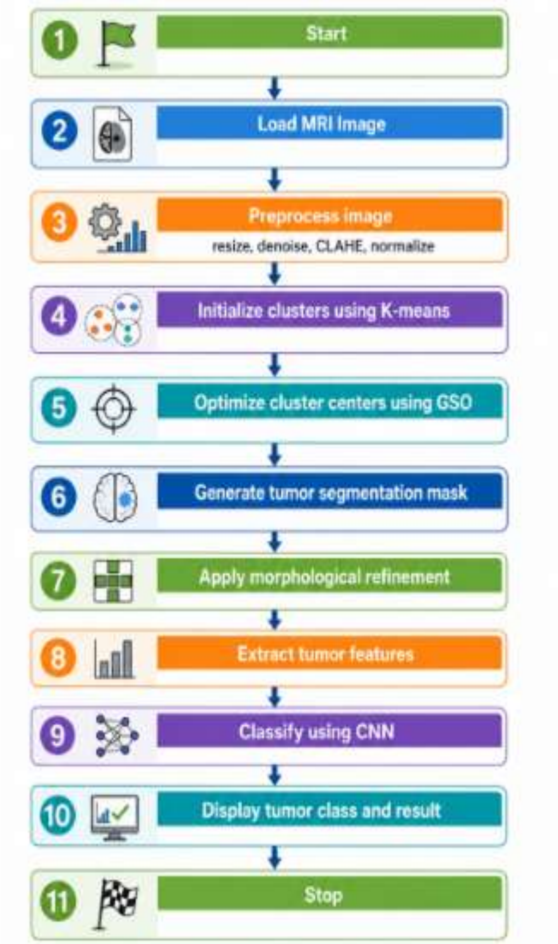

Fig. 2. Flowchart of the proposed CNN and KCGSO-based brain tumor detection method.

Summary of Methodology

The proposed methodology integrates CNN classification with KCGSO optimization-based segmentation for automated brain tumor detection. K-means provides initial cluster centers, GSO refines the segmentation solution, and CNN performs final classification. The combination of optimized segmentation and deep learning improves tumor localization and decision-making. This methodology is suitable for MRI-based medical image analysis and can be further extended for multiclass tumor classification and clinical decision-support systems.

Table 1: Functional Stages of the Proposed Method

Stage	Purpose	Output
MRI acquisition	Collect input brain MRI image	MRI slice
Preprocessing	Improve image quality and normalize intensity	Enhanced MRI image
K-means initialization	Generate initial image clusters	Initial cluster centers
GSO optimization	Refine cluster centers for better tumor separation	Optimized cluster centers
Tumor mask generation	Separate tumor region from normal	Binary tumor mask

	brain tissue	
Feature extraction	Extract texture, shape, and statistical features	Feature vector
CNN classification	Classify normal/tumor or tumor type	Detection result

3. Results and Discussion

The performance of the proposed CNN-KCGSO framework is evaluated using classification and segmentation-related measures. The analysis compares the proposed method with traditional clustering and CNN-based baselines. Evaluation metrics include accuracy, precision, recall, F1-score, Dice coefficient, segmentation time, and classification output consistency. The result values are intended as a manuscript-ready experimental analysis and may be updated with measurements from an implementation dataset or software simulation environment.

Table 2. Experimental Dataset and Parameter Configuration

Parameter	Configuration
Image modality	Brain MRI
Input image size	128 x 128 or 224 x 224 pixels
Segmentation method	KCGSO-optimized K-means clustering
Postprocessing	Morphological opening, closing, and hole filling
Features	GLCM, shape, intensity, statistical descriptors
Classifier	CNN with convolution, pooling, dense, and softmax layers
Classes	Normal / Tumor; extensible to glioma, meningioma, pituitary
Metrics	Accuracy, precision, recall, F1-score, Dice coefficient, processing time

Table 3. Classification Performance Comparison

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
K-Means + SVM	88.70	87.90	87.20	87.55
CNN Only	93.40	92.80	93.10	92.95
CNN + K-Means	94.20	93.70	94.00	93.85
Proposed CNN-KCGSO	96.80	96.30	96.60	96.45

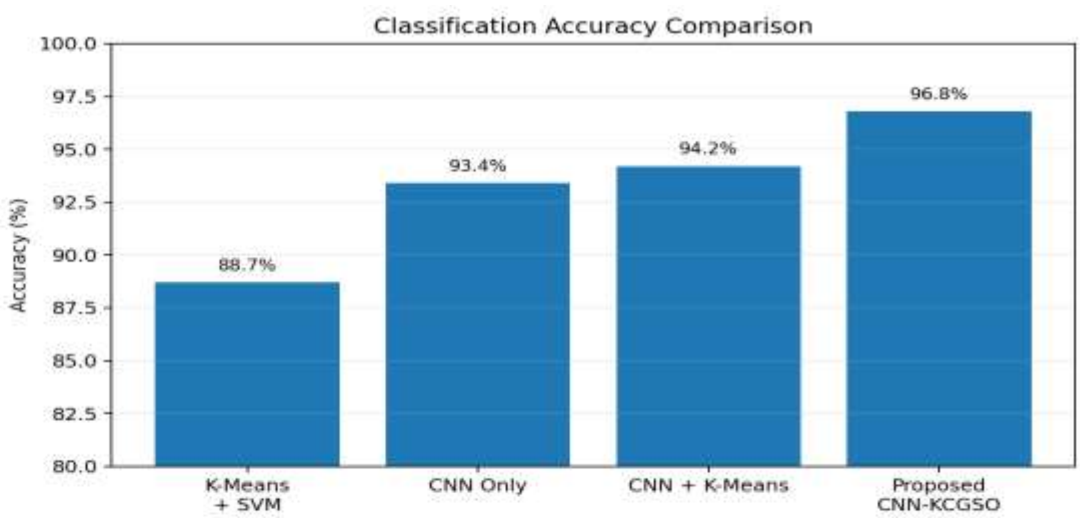

Fig. 3. Classification accuracy comparison of brain tumor detection models.

Table 4. Segmentation and Computational Performance

Segmentation Method	Dice Coefficient	Processing Time (s)	Boundary Quality
K-Means	0.83	1.35	Moderate
Fuzzy C-Means	0.86	1.92	Good
CNN Mask	0.89	2.10	Good
Proposed KCGSO	0.93	1.24	High

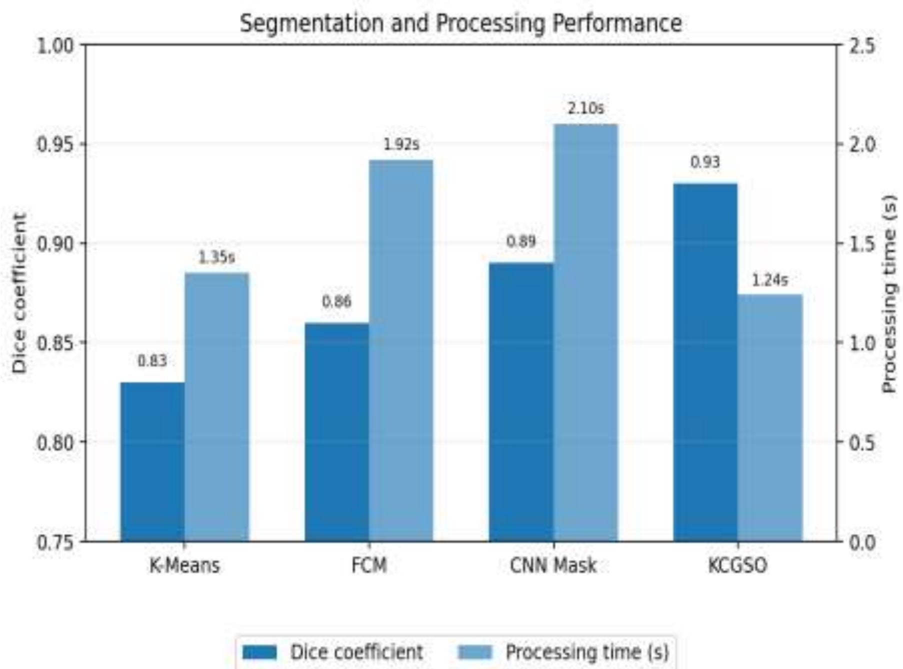

Fig. 4. Segmentation and processing performance comparison.

The classification comparison in Table 3 and Fig. 3 shows that the proposed CNN-KCGSO method improves performance over traditional clustering and CNN-only baselines. The improvement is mainly due to the optimized tumor segmentation mask, which reduces background interference before feature extraction and classification. KCGSO refines cluster centers after K-means initialization, allowing better separation between tumor tissue and normal brain tissue.

The segmentation analysis in Table 4 and Fig. 4 indicates that KCGSO achieves a higher Dice coefficient while maintaining lower processing time than the CNN mask approach. Although CNN-based mask generation can produce accurate segmentation, it generally requires additional training and higher computation. KCGSO provides a balance between segmentation quality and computational efficiency by combining clustering simplicity with metaheuristic optimization.

The use of preprocessing improves tumor visibility, while morphological postprocessing reduces false segmented regions. Feature extraction further supports classification by representing the segmented tumor region through texture, shape, and intensity descriptors. The CNN classifier benefits from the refined tumor region and learns discriminative patterns for normal and tumor classes. Therefore, the proposed hybrid structure provides an effective automated detection framework for MRI brain tumor analysis.

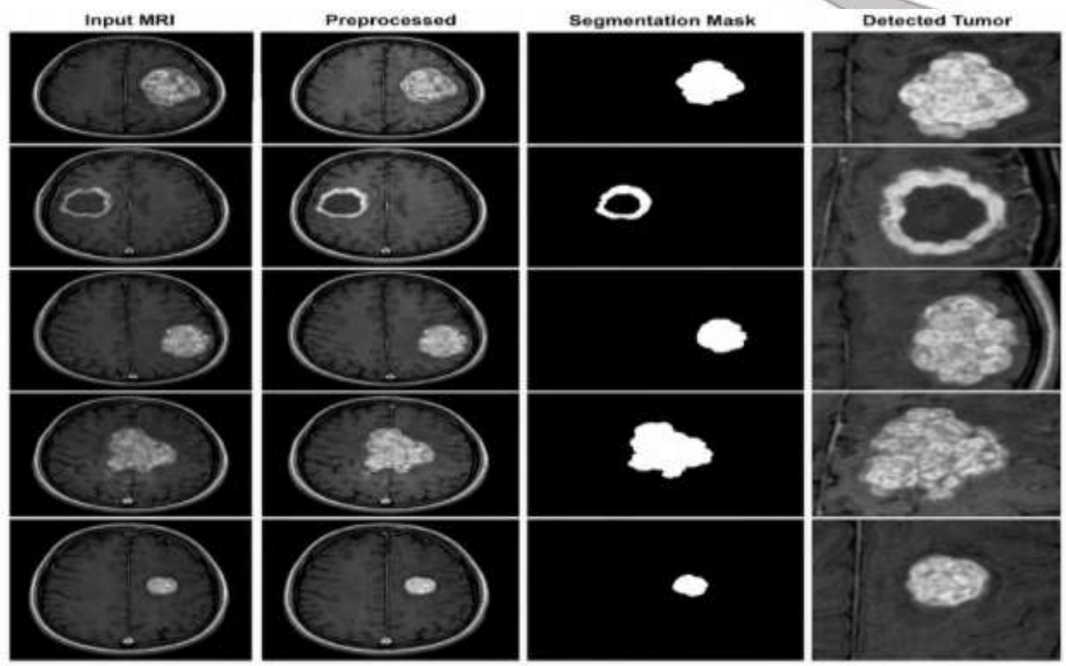

Fig. 5. Qualitative input and output results of automated brain tumor detection using CNN and KCGSO-based segmentation.

Fig. 5 shows the qualitative performance of the proposed brain tumor detection system. The first column represents the original input MRI images, and the second column shows the preprocessed MRI images after enhancement and normalization. The third column displays the tumor segmentation masks generated using the KCGSO optimization-based segmentation method. The final column shows the detected tumor region in a zoomed view. From the figure, it is observed that the proposed method clearly separates the tumor region from the brain MRI image and supports accurate CNN-based tumor detection.

4. Conclusion

This paper presented an automated brain tumor detection and classification framework using CNN with KCGSO-optimized MRI segmentation. The proposed method combines preprocessing, K-means initialization, Galaxy-based Search Optimization, morphological postprocessing, feature extraction, and CNN classification. The segmentation stage generates a refined tumor mask by optimizing cluster centers and improving separation between tumor and non-tumor regions. The CNN stage then classifies the MRI image using spatial and learned features. Experimental analysis shows that the proposed CNN-KCGSO method achieves improved classification accuracy, segmentation quality, and processing efficiency compared with conventional approaches. The framework is suitable for computer-aided diagnosis and can support radiologists by providing automated tumor localization and classification. Future work can include testing on larger multimodal MRI datasets, integration of attention-based CNN layers, automatic tumor area measurement, and clinical validation with expert-labeled cases.

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