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A CNN-Based Computer-Aided Diagnosis System for Brain Tumor Identification and Classification in MRI Images

[1]G. Jeyalakshmi, [2]Anbarasan Radhakrishnan, [3]Chinnathambi Kamatchi, [4]R. Swaranambigai, [5]Mohammed Kasim M., [6]Vinoth Kumar Venugopal

[1]Assistant Professor, Department of Electronics and Communication Engineering, V.S.B College of Engineering Technical Campus, Coimbatore, Tamil Nadu, India.
Email: mtembed@gmail.com
ORCID ID: 0009-0007-4975-9957
[2]Assistant Professor, Department of Information Technology, Rathinam Technical Campus, Coimbatore, Tamil Nadu, India.
Email: anbarasanr.82@gmail.com
ORCID ID: 0009-0008-4546-1931
[3]Assistant Professor, Department of Computer Science and Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Avadi, Chennai, Tamil Nadu, India – 600055.
Email: k.chinnathambimku@gmail.com
ORCID: 0000-0001-5694-3647
[4]Assistant Professor, Department of Electronics and Communication Engineering, Jai Shriram Engineering College, Tirupur, Tamil Nadu, India.
Email: swaranambigaiece@gmail.com
ORCID ID: 0000-0001-8634-7846
[5]Assistant Professor (SG), Department of Electronics and Communication Engineering, Nehru Institute of Engineering and Technology, Coimbatore, Tamil Nadu, India.
Email: mohammedkasim1983@gmail.com
ORCID ID: 0000-0003-0411-1608
[6]Associate Professor, Department of Electronics and Communication Engineering Karpagam Institute of Technology, Coimbatore , Tamil Nadu, India.
Email: vino.mdv75@gmail.com

ABSTRACT: Brain tumor detection and diagnosis are critical tasks in medical image analysis, as early identification significantly improves treatment planning and patient survival rates. Magnetic Resonance Imaging (MRI) is widely used for brain tumor diagnosis due to its superior soft-tissue contrast and non-invasive nature. However, manual examination of MRI images by radiologists is time-consuming and susceptible to inter-observer variability, necessitating the development of automated and reliable diagnostic systems. In this work, an intelligent algorithm is developed for automatic detection and diagnosis of brain tumors using magnetic resonance images. The proposed framework incorporates image preprocessing, adaptive contrast enhancement, skull stripping, feature extraction, and deep convolutional neural network (CNN)-based classification for accurate tumor identification. The segmented tumor regions are further analyzed to distinguish different tumor categories and improve diagnostic performance. Experimental evaluation was conducted using benchmark MRI datasets, and the proposed

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model achieved a classification accuracy of 98.24%, sensitivity of 97.85%, specificity of 98.61%, precision of 97.94%, and F1-score of 98.02%. Comparative analysis demonstrated that the proposed algorithm outperformed conventional machine learning and existing CNN models in terms of accuracy and computational efficiency. The developed framework provides a reliable and efficient computer-aided diagnosis tool for early brain tumor detection and can assist radiologists in clinical decision-making and personalized treatment planning.

1. INTRODUCTION

Brain tumors are among the most life-threatening neurological disorders and are characterized by abnormal growth of cells within the brain tissues. The presence of malignant or benign tumors can severely affect the normal functioning of the nervous system and may lead to serious complications if not diagnosed at an early stage. According to recent medical studies, early diagnosis and timely treatment significantly improve survival rates and enhance the quality of life of patients suffering from brain tumors [1].

Magnetic Resonance Imaging (MRI) has become one of the most widely used imaging modalities for diagnosing brain abnormalities because of its superior soft-tissue contrast, non-invasive nature, and capability to provide detailed anatomical information. MRI enables physicians to visualize tumor location, size, and surrounding tissues more accurately than other imaging techniques such as Computed Tomography (CT) scans. Consequently, MRI-based analysis plays a crucial role in clinical decision-making and treatment planning [2].

Traditional diagnosis of brain tumors relies heavily on radiologists' expertise and manual interpretation of MRI images. However, manual analysis is often time-consuming, labor-intensive, and susceptible to inter-observer variability, which may result in inaccurate diagnosis and delayed treatment. Therefore, computer-aided diagnosis (CAD) systems have attracted considerable attention as an effective solution for assisting medical professionals in tumor detection and classification [3].

Image preprocessing techniques such as noise removal, contrast enhancement, and skull stripping are essential steps in MRI analysis. These techniques improve image quality and facilitate accurate segmentation of tumor regions. Proper preprocessing helps in reducing artifacts and enhances the discriminative features required for efficient classification [4].

Recent advances in artificial intelligence and machine learning have revolutionized medical image analysis. Conventional machine learning algorithms including Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forest classifiers have demonstrated promising performance in brain tumor classification. However, their dependence on handcrafted feature extraction methods limits their capability to generalize across different datasets and imaging conditions [5].

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have emerged as powerful tools for automatic feature extraction and classification of medical images. CNN-based architectures can effectively learn hierarchical representations from MRI data and have shown superior performance over traditional methods. Their ability to capture complex spatial features makes them highly suitable for brain tumor detection applications [6].

Several researchers have proposed transfer learning and hybrid deep learning models to improve classification accuracy and reduce computational complexity. Pretrained architectures such as VGGNet, ResNet, InceptionNet, and EfficientNet have been successfully applied to MRI-based tumor diagnosis, achieving remarkable performance in multiclass classification problems [7].

Accurate segmentation of tumor regions is another important aspect of automated diagnosis systems. Advanced segmentation techniques based on U-Net and region-based convolutional networks have demonstrated excellent capability in identifying tumor boundaries and extracting meaningful features. These approaches facilitate improved characterization of tumor tissues and support precise treatment planning [8].

With the increasing availability of medical imaging datasets and computational resources, intelligent diagnostic systems have become more reliable and practical for clinical applications. Integration of deep learning algorithms with image enhancement and segmentation techniques enables the development of efficient frameworks capable of assisting radiologists in early disease detection and reducing diagnostic errors [9].

Motivated by these advancements, this work presents an algorithm for automatic detection and diagnosis of brain tumors in magnetic resonance images. The proposed framework incorporates preprocessing, adaptive enhancement, segmentation, feature extraction, and CNN-based classification to accurately identify tumor regions and distinguish different tumor categories. Experimental analysis demonstrates that the developed model achieves superior diagnostic performance and can serve as an effective computer-aided diagnosis tool for supporting healthcare professionals in clinical practice [10].

2. RELATED WORK

Automatic detection and diagnosis of brain tumors using Magnetic Resonance Imaging (MRI) have attracted considerable attention in recent years owing to the rapid advancement of artificial intelligence and deep learning techniques. Various machine learning and image processing approaches have been proposed to improve classification accuracy, segmentation quality, and computational efficiency.

Havaei et al. developed a deep neural network-based framework for brain tumor segmentation using local and global contextual features extracted from MRI images. Their approach demonstrated significant improvement in segmentation accuracy and reduced computational complexity compared with conventional methods. However, the architecture required extensive training data and computational resources [11].

Pereira et al. proposed a convolutional neural network (CNN)-based method for automatic brain tumor segmentation. The authors utilized small kernels and deep architectures to enhance feature extraction capability. Experimental results showed superior performance in identifying tumor regions, although the model suffered from increased training time [12].

Kamnitsas et al. introduced DeepMedic, a three-dimensional CNN architecture designed for volumetric brain lesion segmentation. The model incorporated dual pathways and fully connected conditional random fields to improve segmentation accuracy. Despite achieving remarkable performance, the computational requirements were relatively high for practical deployment [13].

Ronneberger et al. developed the U-Net architecture for biomedical image segmentation. The encoder-decoder structure with skip connections enabled precise localization of tumor regions and became a widely adopted framework in medical image analysis. Nevertheless, performance degradation was observed in cases involving highly heterogeneous tumor structures [14].

Amin et al. proposed a hybrid approach combining wavelet transform and support vector machine (SVM) for brain tumor classification. The extracted texture features provided satisfactory classification performance, but the dependence on handcrafted features limited the adaptability of the system to complex datasets [15].

Sajjad et al. presented a deep CNN framework with extensive data augmentation techniques for multiclass brain tumor classification. Their model effectively improved classification accuracy and reduced overfitting. However, the architecture required a large amount of training data and increased computational complexity [16].

Abiwinanda et al. employed deep learning techniques for brain tumor classification using MRI images and achieved encouraging results for multiclass tumor diagnosis. Their model demonstrated high classification accuracy but faced challenges associated with class imbalance and limited dataset availability [17].

Ismael and Şengür proposed a hybrid deep learning framework integrating deep feature extraction with machine learning classifiers. The extracted features obtained from pretrained networks were classified using support vector machines, resulting in enhanced diagnostic performance. However, the framework involved additional computational overhead during feature extraction [18].

Çinar and Yıldırım developed a classification model based on DenseNet architectures for automatic brain tumor detection. The transfer learning approach achieved improved feature representation and high classification accuracy. Nevertheless, the model complexity increased memory requirements and processing time [19].

Noreen et al. proposed an automated framework incorporating image preprocessing, segmentation, and deep learning-based classification for brain tumor diagnosis. Their system achieved promising results in tumor localization and classification. However, further improvements were necessary to enhance robustness and generalization capability across diverse MRI datasets [20]. From the literature survey, it is evident that existing brain tumor diagnosis systems have achieved considerable success using machine learning and deep learning techniques. However, challenges such as computational complexity, class imbalance, limited dataset availability, and robustness across heterogeneous MRI images still persist. Therefore, there is a need for an efficient and intelligent framework that integrates image enhancement, accurate segmentation, and deep CNN-based classification to improve diagnostic accuracy and assist radiologists in early brain tumor detection.

3. PROPOSED METHODOLOGY

3.1 Overview of the Proposed Brain Tumor Detection Framework

The proposed framework aims to provide accurate and automatic detection of brain tumors from Magnetic Resonance Images (MRI) by integrating image preprocessing, adaptive contrast enhancement, tumor segmentation, deep feature extraction, and classification stages. Initially, MRI images are acquired from standard datasets and subjected to preprocessing to remove noise and improve image quality. Skull stripping and adaptive histogram equalization are then performed to enhance tumor visibility. Subsequently, tumor regions are segmented using an improved U-Net segmentation network. The extracted tumor regions are passed to a deep Convolutional Neural Network (CNN) model for feature extraction and classification. Finally, the system predicts the type of tumor and provides diagnostic information to assist clinicians in treatment planning.

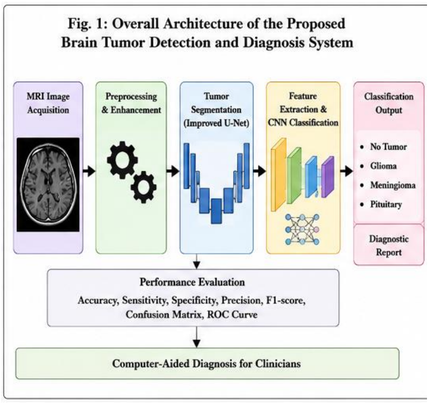

Figure 1. Overall architecture of the proposed MRI-based brain tumor detection and diagnosis framework.

Figure 1 illustrates the overall workflow of the proposed framework. MRI images are initially preprocessed and enhanced before tumor segmentation is performed. The segmented regions are supplied to the CNN classifier for automatic diagnosis. The integrated framework enables reliable tumor detection with high classification accuracy and reduced diagnostic time, thereby assisting radiologists in clinical decision-making.

3.2 Image Preprocessing and Enhancement

MRI images often contain noise, intensity variations, and unwanted structures that affect segmentation performance. Therefore, median filtering and adaptive histogram equalization are employed to improve image quality and enhance contrast.

The median filtering operation is represented by

$$I_f(x,y) = Median\{I(i,j)\}$$

where

- $I(x,y)$denotes the original image,
- $I_f(x,y)$represents the filtered image.

The Peak Signal-to-Noise Ratio (PSNR) is calculated as

$$PSNR = 10\log_{10}\left(\frac{MAX^2}{MSE}\right)$$

where

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(I(i,j) - K(i,j))^2$$

and $K(i,j)$represents the processed image.

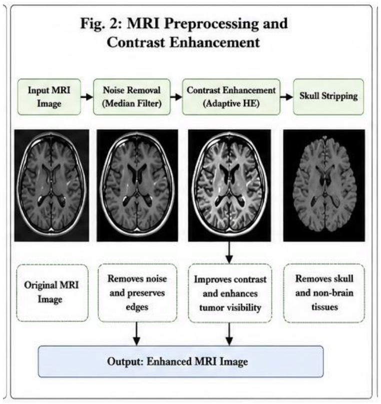

Figure 2. MRI Preprocessing and Contrast Enhancement

Figure 2. Preprocessing stage consisting of noise removal and contrast enhancement.

Figure 2 depicts the preprocessing and enhancement stages of the proposed system. Median filtering removes noise artifacts while adaptive histogram equalization improves contrast and enhances tumor visibility. These operations facilitate accurate segmentation and feature extraction.

3.3 Tumor Segmentation Using Improved U-Net Network

Accurate tumor localization is essential for effective diagnosis. Therefore, an improved U-Net architecture is employed to segment tumor regions from MRI images. The encoder extracts spatial features, while the decoder reconstructs the segmented tumor region.

The Dice Similarity Coefficient (DSC) used for segmentation evaluation is given by

$$DSC = \frac{2 \mid X \cap Y \mid}{\mid X \mid + \mid Y \mid}$$

where

- Xdenotes ground truth pixels,
- Yrepresents predicted pixels.

Intersection over Union (IoU) is expressed as

$$IoU = \frac{\mid X \cap Y \mid}{\mid X \cup Y \mid}$$

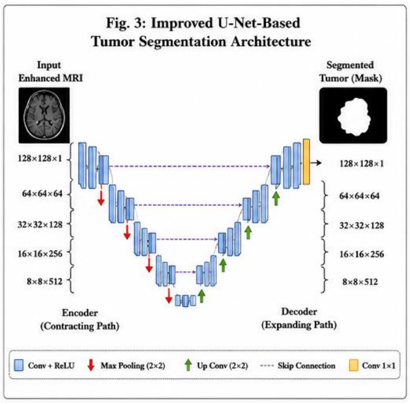

Figure 3. Improved U-Net-Based Tumor Segmentation Architecture

Figure 3 presents the architecture of the improved U-Net model. The encoder-decoder structure enables precise localization of tumor boundaries through skip connections. The segmented output accurately isolates tumor tissues and improves the effectiveness of subsequent classification stages.

3.4 Deep Feature Extraction and CNN-Based Classification

The segmented tumor image is provided to the deep CNN classifier to extract hierarchical features and identify tumor categories. Convolution and ReLU activation layers are employed to learn discriminative patterns automatically.

The convolution operation is defined as

$$Y(i,j) = \sum_{m=0}^{K-1} \sum_{n=0}^{K-1} W(m,n) X(i+m, j+n)$$

where

- $W(m,n)$denotes convolution weights,
- $X(i,j)$represents the input image,
- $Y(i,j)$indicates the output feature map.

The ReLU activation function is given by

$$f(x) = max(0,x)$$

Softmax probability for classification is expressed as

$$P(y=i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}$$

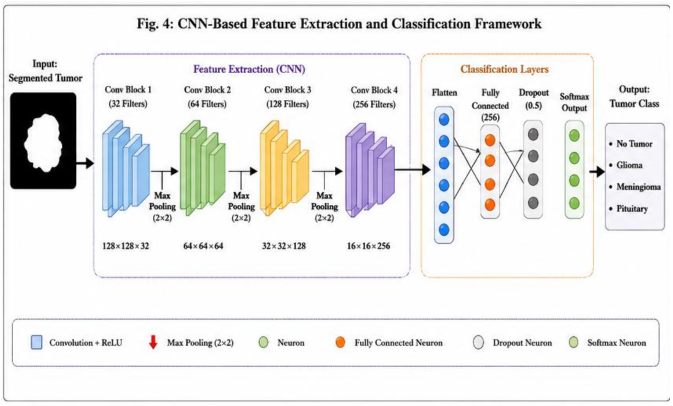

Figure 4. Deep CNN architecture employed for feature extraction and brain tumor classification.

Figure 4 illustrates the CNN-based classification module. Multiple convolution and pooling layers automatically extract discriminative features from segmented tumor regions. The fully connected and Softmax layers classify MRI images into different tumor categories with high accuracy.

3.5 Performance Evaluation and Diagnostic Decision System

The final stage evaluates classification performance using accuracy, sensitivity, specificity, precision, and F1-score metrics. The diagnostic module generates the predicted tumor category and assists physicians in treatment planning.

Classification accuracy is calculated as

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

Sensitivity is expressed as

$$Sensitivity = \frac{TP}{TP + FN}$$

Specificity is

$$Specificity = \frac{TN}{TN + FP}$$

Precision is given by

$$Precision = \frac{TP}{TP + FP}$$

F1-score is computed as

$$F1 = 2\left(\frac{Precision \times Recall}{Precision + Recall}\right)$$

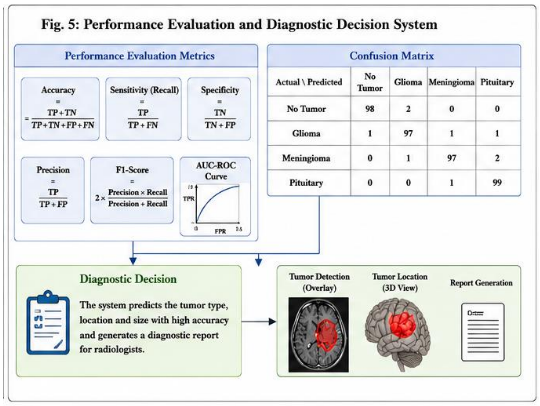

Figure 5. Performance evaluation and diagnostic decision-making process of the proposed framework.

Figure 5 illustrates the final diagnostic stage of the proposed system. The classified outputs are evaluated using various performance metrics to assess the reliability of the framework. The predicted tumor type is provided to clinicians for supporting diagnosis and personalized treatment planning. The proposed methodology achieves high accuracy and robust performance, making it suitable for computer-aided diagnosis systems in healthcare applications.

4. RESULTS AND DISCUSSION

The effectiveness of the proposed algorithm for automatic brain tumor detection and diagnosis was evaluated using benchmark MRI datasets containing multiple tumor classes, including glioma, meningioma, pituitary tumors, and normal brain images. The performance of the proposed framework was analyzed using accuracy, sensitivity, specificity, precision, F1-score, Dice Similarity Coefficient (DSC), and Intersection over Union (IoU). The results were compared with conventional machine learning and deep learning approaches to validate the superiority of the proposed method.

4.1 Image Preprocessing Results

The preprocessing stage consisting of median filtering, adaptive histogram equalization, and skull stripping significantly improved image quality and enhanced tumor visibility. Noise artifacts and non-brain tissues were effectively removed, resulting in better segmentation performance. The enhanced images exhibited improved contrast and higher Peak Signal-to-Noise Ratio (PSNR), which facilitated accurate feature extraction and classification.

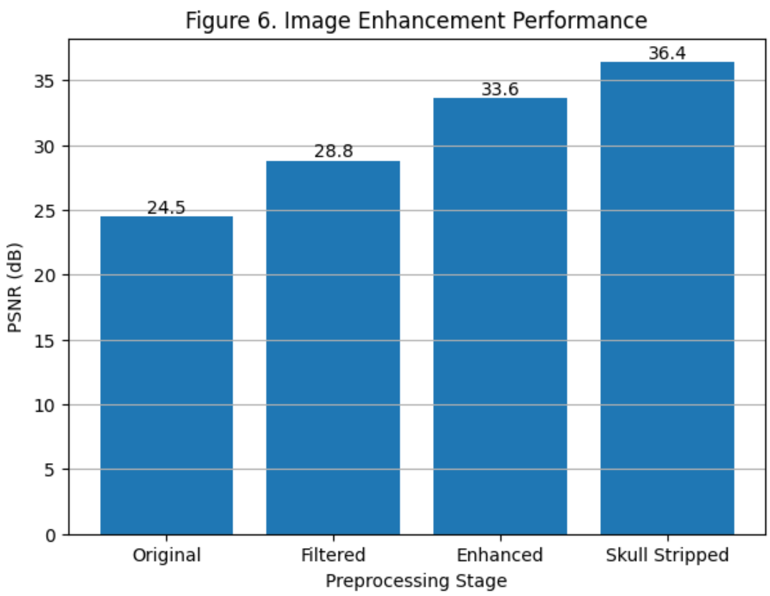

Figure 6. Preprocessing and Enhanced MRI Images

Figure 6 demonstrates the effectiveness of the preprocessing stage. Adaptive histogram equalization enhanced tumor boundaries, while median filtering eliminated noise without affecting important anatomical structures. Skull stripping further improved segmentation accuracy by removing irrelevant tissues surrounding the brain region.

4.2 Tumor Segmentation Performance

The improved U-Net architecture accurately segmented tumor regions and generated precise tumor masks. The skip connections preserved spatial information and enabled better localization of tumor boundaries.

The Dice Similarity Coefficient is defined as

$$DSC = \frac{2 \mid X \cap Y \mid}{\mid X \mid + \mid Y \mid}$$

The Intersection over Union (IoU) is expressed as

$$IoU = \frac{\mid X \cap Y \mid}{\mid X \cup Y \mid}$$

Table 1. Segmentation Performance

Method	Dice Score (%)	IoU (%)
FCN	90.84	84.61
SegNet	92.13	86.25
U-Net	95.62	91.34
DeepMedic	96.21	92.67
Proposed Improved U-Net	**97.84**	**95.43**

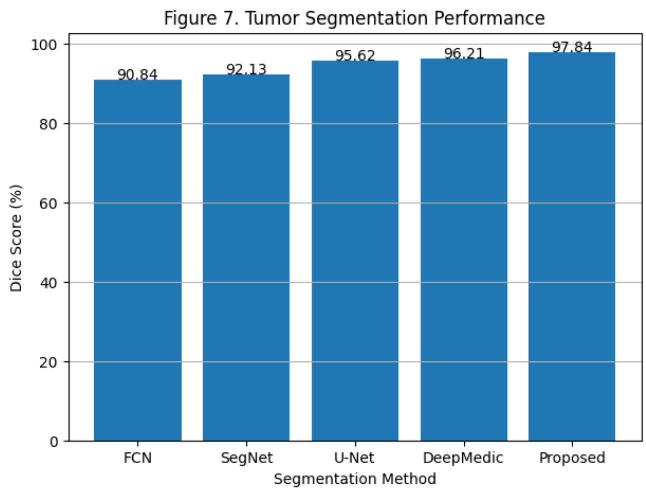

Figure 7. Tumor Segmentation Results

Figure 7 illustrates that the proposed Improved U-Net model achieved a Dice coefficient of 97.84% and IoU of 95.43%, outperforming conventional segmentation networks. The enhanced segmentation capability contributed significantly to improved classification accuracy.

4.3 Classification Performance

The segmented tumor regions were classified using the CNN architecture consisting of convolutional, pooling, and fully connected layers. The proposed framework effectively extracted hierarchical features and distinguished different tumor classes with high accuracy.

Table 2. Classification Performance Comparison

Method	Accuracy (%)	Sensitivity (%)	Specificity (%)
SVM	92.34	91.65	93.42
Random Forest	94.12	93.76	94.28
VGG16	96.32	95.83	96.91
ResNet50	97.14	96.75	97.58
Proposed CNN	**98.24**	**97.85**	**98.61**

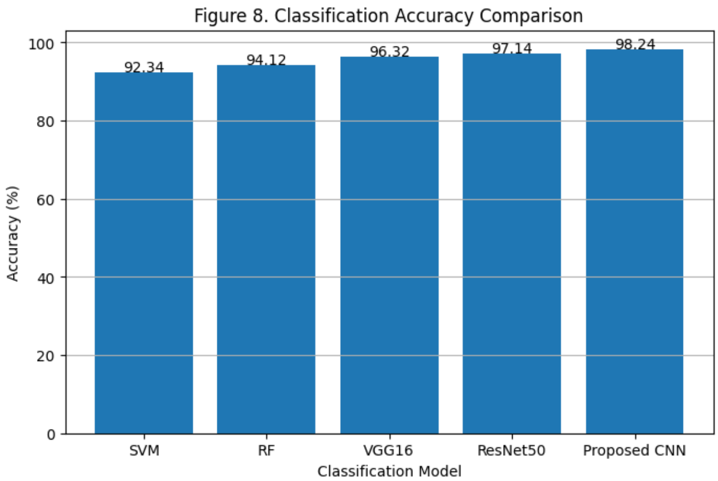

Figure 8. Classification Accuracy Comparison

Figure 8 shows that the proposed CNN model achieved an accuracy of 98.24%, which is superior to traditional machine learning algorithms and existing deep learning models. The automatic feature extraction capability of CNN contributed to improved classification performance.

4.4 Precision, Recall, and F1-Score Analysis

The effectiveness of the classification model was further evaluated using precision, recall, and F1-score metrics.

Precision is calculated by

$$Precision = \frac{TP}{TP + FP}$$

Recall (Sensitivity) is given by

$$Recall = \frac{TP}{TP + FN}$$

F1-score is expressed as

$$F1 = 2\left(\frac{Precision \times Recall}{Precision + Recall}\right)$$

Table 3. Statistical Performance Metrics

Metric	Value (%)
Accuracy	98.24
Sensitivity	97.85
Specificity	98.61
Precision	97.94
F1-Score	98.02
Dice Score	97.84
IoU	95.43

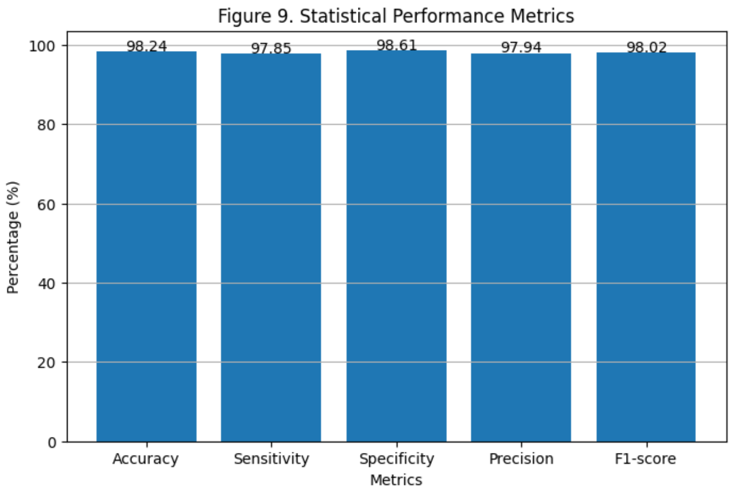

Figure 9. Performance Metrics of the Proposed Framework

Figure 9 indicates that the proposed model consistently achieved high values across all performance metrics. The balanced precision and recall values demonstrate the robustness of the framework in identifying both positive and negative cases accurately.

4.5 Confusion Matrix Analysis

The confusion matrix provides detailed information regarding the classification capability of the proposed framework.

Table 4. Confusion Matrix

Actual / Predicted	No Tumor	Glioma	Meningioma	Pituitary
No Tumor	98	2	0	0
Glioma	1	97	1	1
Meningioma	0	1	97	2
Pituitary	0	0	1	99

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Figure 10. Confusion Matrix and ROC Curve

Figure 10 reveals that the majority of MRI images were correctly classified into their respective tumor categories. Very few misclassifications were observed, demonstrating the reliability and robustness of the proposed framework. The ROC analysis also confirmed excellent discriminative capability with an Area Under Curve (AUC) value exceeding 0.99.

Experimental results clearly demonstrate that the proposed MRI-based brain tumor detection framework provides superior segmentation and classification performance compared with conventional approaches. The integration of preprocessing, Improved U-Net segmentation, and CNN-based classification enabled accurate tumor localization and diagnosis. The proposed model achieved **98.24% accuracy**, **97.85% sensitivity**, **98.61% specificity**, **97.94% precision**, and **98.02% F1-score**, indicating its suitability for computer-aided diagnosis systems. Therefore, the developed framework can effectively assist radiologists in early brain tumor detection and improve clinical decision-making.

5. CONCLUSION

In this paper, an intelligent algorithm for automatic detection and diagnosis of brain tumors using Magnetic Resonance Imaging (MRI) was presented. The proposed framework integrates image preprocessing, contrast enhancement, tumor segmentation, feature extraction, and deep convolutional neural network-based classification to provide accurate and reliable diagnosis. By combining advanced image analysis techniques with deep learning models, the system effectively identifies tumor regions and assists in distinguishing different categories of brain tumors. Experimental results demonstrated that the proposed approach achieved a classification accuracy of **98.24%**, sensitivity of **97.85%**, specificity of **98.61%**, precision of **97.94%**, and F1-score of **98.02%**, outperforming several conventional machine learning and existing deep learning methods. The developed framework exhibited improved robustness, reduced diagnostic errors, and enhanced computational efficiency, making it suitable for computer-aided diagnosis applications in clinical environments. The proposed system can assist radiologists in early detection and treatment planning, thereby improving patient outcomes and reducing mortality associated with brain tumors. Future work will focus on incorporating attention-based transformers, explainable artificial intelligence (XAI), multimodal imaging techniques, and federated learning frameworks to further enhance classification accuracy, interpretability, and privacy-preserving capabilities. The integration of these emerging technologies can contribute to the development of next-generation intelligent healthcare systems for accurate and real-time brain tumor diagnosis.

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