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Enhanced Brain Tumor Detection and Classification in MRI: A CNN and Morphological Feature Approach

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Abstract: *The number of diseases associated with brain tumors has increased significantly over the past few years, making them the tenth most common cancer affecting children and adults. Because brain tumors vary in size, mass, and location, brain diagnosis and classification are the most important and time-consuming tasks in diagnosis. Magnetic Resonance Imaging (MRI) is widely used to diagnose tumors and various soft tissue abnormalities in many diseases. Examining the size and location of brain tumors plays an important role in brain diagnosis. In this paper, a deep learning method is used to segment and classify brain tumors via MRI. Firstly, the image is preprocessed using image enhancement using a median and bilateral filter. Binary threshold is then used for segmentation. Morphological functions are used for feature extraction. Finally, Convolutional Neural Network (CNN) is used to predict whether the brain MRI was normal or abnormal. Multiple brain MRIs are used, including tumor and healthy brain images, to train the model and the model achieves 96% accuracy.*
Keywords: *brain tumor, CNN, MRI, Deep Learning.*

1. INTRODUCTION

Given that the brain is the most intricate organ in the human body, brain tumors represent one of the most severe forms of cancer. A brain tumor is a cluster of abnormal brain cells, which can cause significant pain and problems as they grow, due to the rigid skull that encases the brain. These tumors can be classified as benign (non-cancerous) or malignant (cancerous) [1]. Regardless of their classification, the growth of these tumors within the skull can be life-threatening and cause substantial damage to brain function. The proliferation of these abnormal cells, whether benign or malignant, poses a significant risk to the overall health and functionality of the brain [2],[3].

Brain tumors are classified into two types: primary and secondary tumors. Primary tumors originate in the brain and can be either benign or malignant. Secondary tumors, also known as metastatic brain tumors, arise when cancer cells spread to the brain from other parts of the body, such as the lungs, breasts, skin, or kidneys, and are always malignant. Unlike malignant tumors, benign tumors do not metastasize to other parts of the body. Accurate diagnosis of brain tumors is essential for effective treatment planning and reducing mortality rates. Imaging techniques play a crucial role in diagnosing brain tumors, providing detailed information necessary for appropriate medical intervention [4], [5].

When it comes to diagnosing brain illnesses, MRI is a very useful technique because it provides more detailed information than CT scans. Determining the tumor's size, location, and features is essential when performing brain scans. For neurosurgeons to accurately diagnose patients and determine the best course of treatment, this information is essential. Strong magnetic fields and radio waves are used in MRI, a medical imaging method that creates detailed images of the body's internal structures and physiological processes. This non-invasive technique is essential for the detection and treatment of brain cancers because it makes it possible to precisely visualize abnormalities in the brain [6].

With MRI, it facilitates imaging of anatomical structures in three different planes: sagittal, coronal and axial. There are three types of magnetic resonance imaging sequences: T1-weighted, T2-weighted, and fluid-attenuated inversion (Flair). Most sequences are T1-weighted and T2-weighted scans. When looking at MRI brain images, radiologists pay particular attention to three specific areas of the brain such as grey matter (GM), white matter (WM), and cerebrospinal fluid space (CSF) [7].
The use of MRI images to diagnose brain cancers is essential because it streamlines data processing by emphasizing precise, high-resolution scans. In this paper, a deep convolutional neural network (CNN) method is proposed for brain tumor detection, segmentation, and classification model. This method improves the efficacy of diagnosis and treatment planning by utilizing the detailed imaging offered by MRI to precisely identify and study brain tumors.

2. LITERATURE SURVEY

Research work by different authors has been discussed on the basis of varied deep learning techniques and architectures adopted by them.
Sakshi Ahuja et al., used transfer learning and super-pixel technique for detection of brain tumor and brain segmentation respectively. The dataset used was from BRATS 2021 brain tumor segmentation challenge and this model was trained on the VGG 19 transfer learning model. Using the super-pixel technique the tumor was divided between LGG and HGG images. This resulted in an average of dice index of 0.934 in opposition to ground truth data [8].
Hajar Cherguif et al., used U-Net for the semantic segmentation of medical images. To develop a good convoluted 2D segmentation network, U-Net architecture was used. BRATS 2022 dataset was used for testing and evaluating the model proposed. The U-Net architecture proposed had 27 convolutional layers, 4 deconvolutional layers, Dice coefficient of 0.81 [9].
Chirodip Lodh Choudhury et al., made the use of deep learning techniques involving deep neural networks and also incorporated it with a Convolutional Neural Network model to get the accurate results of MRI scans. A 3-layer CNN architecture was proposed which was further connected to a fully Connected Neural Network. F-score equal to 97.33 and an accuracy equal to 96.05% was achieved [10].
Ahmad Habbie et al., used MRI T1 weighted images and using semi-automatic segmentation analyzed the possibility of a brain tumor using an active contour model. The performance of morphological active contour without edge, snake active contour and morphological geodesic active contour was analyzed. MGAC performed the best among all three as suggested by the data [11].
Neelum et al., used a deep learning concatenation approach to detect the possibility of having a brain tumor. Pre trained deep learning models which are Inception - v3 and DenseNet201 were used to detect and classify brain tumors. Inception - v3 model was pre trained to extract the features and these features were concatenated for tumor classification. Then, the classification part was done by a softmax classifier [12].
wati Jayade et al., used Hybrid Classifiers. The classification of tumors was done into types, malignant and benign. Feature dataset here was prepared by Gray level Co-occurrence Matrix (GLCM) feature extraction method. A hybrid method of classifiers involving KNN and SVM classifiers was proposed to increase efficiency [13].
M. S. Ahmed et al., implemented a pipeline for classifying abnormal structures in MRI images of the brain, utilizing Support Vector Machine (SVM) in combination with Probabilistic Neural Network (PNN) for classification. It emphasized the automated detection of brain tumors, achieving a good accuracy in distinguishing healthy and tumorous tissue [14].
A Gabor transform along with the soft and hard clustering for detecting the edges in the CT and MRI images was discussed in the paper. A total of 4500 and 3000 instances of MRI images and CT were used respectively. K-means clustering was used for the separation of similar features into sub-groups. To represent the images in the form of histogram properties, Fuzzy c means method was used [15].
D. A. Sungheetha et al., used a Bayesian approach for the classification of brain tumor using capsule networks was presented in this paper. To improve the results of tumor detection, capsule network was used as CNN can lose the important spatial information. They proposed a BayesCap framework. To test the proposed model they used a benchmark brain tumor dataset [16].

Many other researchers have contributed in identification of brain tumor, regarding the latest research work done in this domain have been reviewed and tabulated in Table 1. Key details such as the dataset and techniques used, observations and accuracy achieved have been presented to aid further research work in this domain.

Brain tumor detection presents a formidable challenge due to the variability in location, shape, and structure among patients, complicating the segmentation process. Furthermore, the diverse anatomical features of the brain across different individuals add another layer of complexity. Tumors themselves can exhibit intricate shapes and structures, often spanning multiple regions within the brain. This complexity underscores the difficulty inherent in automating the segmentation process.

3. METHODOLOGY

In this study, a comprehensive approach is developed for brain tumor segmentation and classification using deep learning techniques. The methodology consists of several key stages, including image acquisition, preprocessing, filtering, enhancement, segmentation, feature extraction, data partitioning, and classification using Convolutional Neural Networks (CNNs). Each stage is crucial to ensure the accurate identification and classification of brain tumors from MRI images as shown in figure 1.

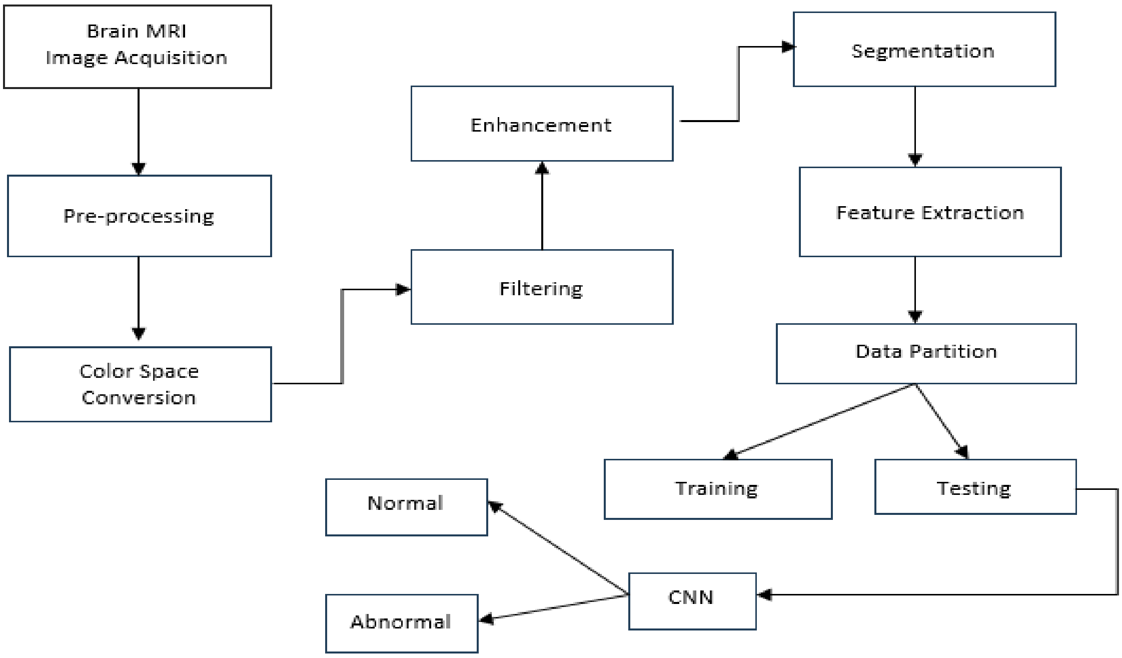

Figure 1: Proposed Methodology for Brain Tumor Classification using CNN

3.1. Image Acquisition

The initial step involves acquiring a suitable dataset of brain MRI images. For this study, the Kaggle Brain MRI dataset was used, which includes a diverse set of approximately 2000 MRI images of normal and abnormal brain scans. The dataset includes T1-weighted axial brain MRI scans with pixel dimensions of 256×256, acquired using standardized protocols with 3T MRI scanners. This dataset serves as the foundation for the subsequent processing and analysis.

3.2. Image Preprocessing

Preprocessing is critical to ensure the images are in an optimal format for analysis by the CNN.

A. Grayscale Conversion: All MRI images are converted from color to grayscale using the cv2.cvtColour function. This step simplifies the image data and reduces computational complexity.

B. Noise Reduction: Noise is removed from the images using a combination of median and bilateral filters: In Median filter a non-linear filter that replaces each pixel's value with the median value of the neighboring pixels. This effectively removes salt-and-pepper noise while preserving edges. To optimize noise reduction, adaptive kernel size is implemented based on image dimension. In Bilateral Filter it smoothens images by averaging pixel values with nearby pixels while maintaining sharp edges, thus reducing noise without blurring important features.

C. Image Resizing: Images are resized to a standard dimension (e.g., 256x256 pixels) to ensure uniformity and compatibility with the input requirements of the CNN model.

D. Data Augmentation: Various augmentation techniques such as rotation, flipping, zooming, and shifting are applied to increase the diversity of the training set and prevent overfitting.

E. Normalization: Pixel values are normalized to a standard range (e.g., 0 to 1) to help in faster and more stable convergence of the model during training. Batch normalization is done after each convolutional layer.

3.3. Color Space Conversion

Images are converted to grayscale if not already done in the preprocessing step. This reduces the complexity of the data and prepares the images for subsequent filtering and enhancement processes.

3.4. Image Filtering

Filtering techniques are applied to remove noise and enhance the quality of the images using median and bilateral filters.

3.5. Image Enhancement

Enhancement techniques are used to improve the visual quality of the images, making them more suitable for segmentation and feature extraction. This involves direct manipulation of pixel values to enhance the structures of interest.

3.6. Segmentation

Segmentation is performed to isolate regions of interest, such as potential tumors, from the background. Initially, binary thresholding is used where pixels below a certain intensity threshold are set to 0 (black) and those above it are set to 255 (white). Advanced segmentation models like U-Net are employed to achieve more accurate and automated tumor segmentation. U-Net is particularly effective for biomedical image segmentation due to its architecture, which captures both context and precise localization.

3.7. Feature Extraction

Morphological operations and deep learning techniques are utilized to extract relevant features from the segmented MRI images. Using morphological operations as dilation, erosion, opening, and closing are applied to enhance the structural details of the tumors, aiding in accurate classification. Later using the pre-trained models on large datasets (e.g., ImageNet) are used to leverage learned features for the MRI classification task. This approach significantly improves the performance of the model by utilizing features already learned from a large amount of data.

3.8. Data Partition

The dataset is divided into training and testing sets. Training set which is used to develop and train the CNN model and the Testing set reserved for evaluating the performance of the trained model.

3.9. Classification

A Convolutional Neural Network (CNN) is designed and implemented to classify the MRI images as normal or abnormal. The architecture of the CNN includes multiple layers:

A. Input Layer: Accepts the preprocessed MRI images.

B. Convolutional Layers: Apply convolutional filters to extract feature maps from the input images.

C. Activation Layers: Introduce non-linearity into the model using activation functions like ReLU (Rectified Linear Unit).

D. Pooling Layers: Perform down-sampling to reduce the dimensionality of the feature maps, which helps in reducing the computational complexity and overfitting.

E. Fully Connected Layers: Integrate the features extracted by the convolutional layers to make final predictions.

F. Output Layer: a softmax activation function is used to classify the images as either normal or abnormal.

The methodology for brain tumor segmentation and classification using deep learning begins with image acquisition, where a suitable dataset of brain MRI images is gathered. Next, image preprocessing is performed, which involves converting images to grayscale, reducing noise, resizing, augmenting, and normalizing pixel values. Following this, color space conversion to grayscale simplifies the data for further analysis. Image filtering using median and bilateral filters removes noise while preserving important features.

Image enhancement techniques are then applied to improve visual quality. The enhanced images undergo segmentation to isolate regions of interest, using methods like binary thresholding and advanced models like U-Net. Feature extraction follows, utilizing morphological operations and transfer learning to capture relevant details. The processed dataset is then partitioned into training and testing sets. Finally, a Convolutional Neural Network (CNN) is implemented, comprising layers for convolution, activation, pooling, and fully connected layers, to classify the MRI images as normal or abnormal. This comprehensive process ensures accurate and effective brain tumor identification and classification as shown in the figure 2.

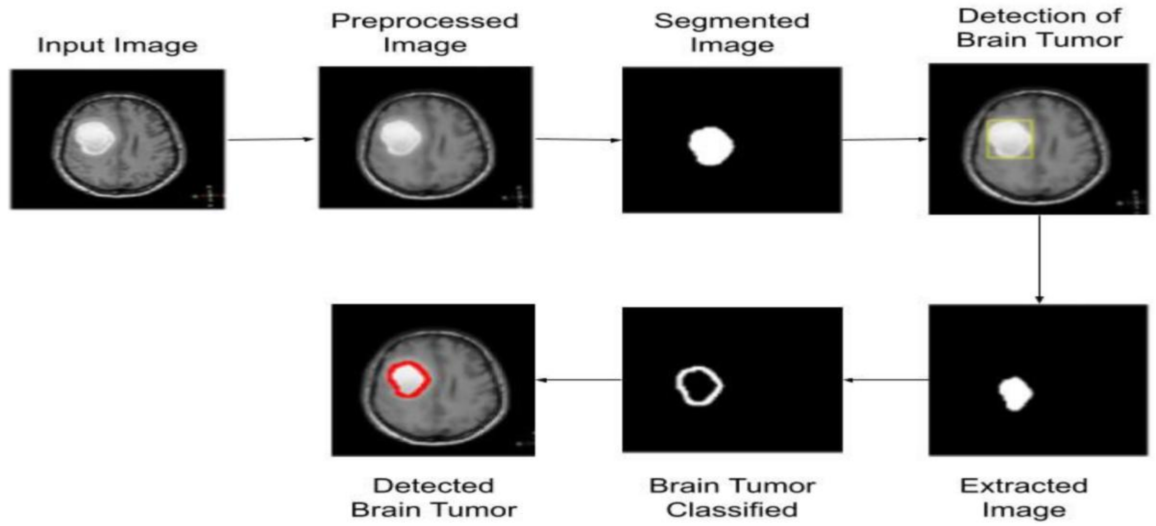

Figure 2: Brain Tumor Identification

4. RESULTS

The CNN model was trained and validated on the Kaggle Brain MRI dataset. During the training phase, the model parameters were optimized to minimize the classification error. The model achieved an accuracy of 96% on the test set, indicating its effectiveness in distinguishing between normal and abnormal brain MRI images. Detailed performance metrics, including the confusion matrix, ROC curve, and AUC, were provided to comprehensively evaluate the model's performance.

The confusion matrix provides a detailed breakdown of a classification model's performance. It tallies the number of correct and incorrect predictions for each class. In brain tumor classification using CNNs, the confusion matrix helps assess the model's ability to identify both normal and abnormal brain scans. Analyzing this matrix allows researchers to see how often the model correctly classified tumors (True Positives) and missed tumors (False Negatives), along with how well it distinguished normal brains (True Negatives) from falsely identifying abnormalities (False Positives) as shown in table1 and figure 3.

Table 1: Confusion Matrix for Brain Tumor Identification

Predicted Class	Normal	Abnormal	Total
Normal	450	20	470
Abnormal	15	515	530
Total	465	535	1000

True Positives (TP): 515
True Negatives (TN): 450
False Positives (FP): 20

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False Negatives (FN): 15

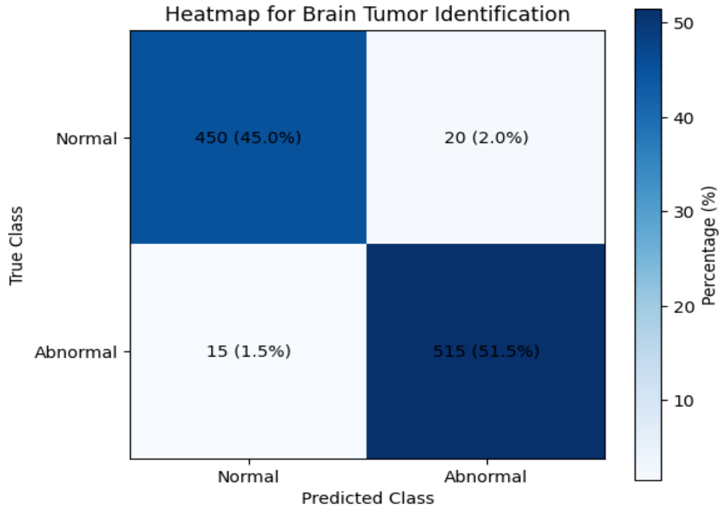

Figure 3: Heatmap for Brain Tumor Identification

Accuracy, a common metric in classification tasks, simply reflects the overall proportion of correct predictions made by the model. In brain tumor classification with CNNs, accuracy tells us the percentage of scans the model classified accurately, encompassing both normal and abnormal brains.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$\text{Accuracy} = \frac{515+450}{515+450+20+15} = 0.965$$

$$\text{Accuracy} = 96.5\%$$

For brain tumor classification using CNNs, precision focuses on the positive class, which is identifying tumors. A high precision value tells us that a significant portion of the scans the model classified as abnormal actually contained tumors (True Positives). Ideally, a high precision value will minimize False Positives, where the model mistakenly identifies a normal brain as cancerous. This reduces unnecessary biopsies and anxieties for patients. However, precision needs to be considered alongside other metrics like recall (True Positive Rate) to ensure the model isn't missing actual tumors. A balanced approach between precision and recall is crucial for reliable brain tumor classification.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Precision} = \frac{515}{515+20} = 0.9626$$

$$\text{Precision} = 96.26\%$$

Recall, plays a vital role in brain tumor classification with CNNs. It zooms in on the positive class (tumors) and tells us how many actual tumors the model correctly identified. A high recall signifies the model's ability to capture most of the existing tumors (minimizing False Negatives). This is critical for early detection and treatment of brain tumors. Unlike accuracy, recall prioritizes not missing tumors even if it means some normal scans are misclassified (False Positives). In a clinical setting, a missed tumor can have severe consequences. However, recall needs to be balanced with precision.

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

$$\text{Recall} = \frac{515}{515 + 15} = 0.9726$$

$$\text{Recall} = 97.26\%$$

The F1 score is a crucial metric for evaluating the performance of CNN models in brain tumor classification, as it balances precision and recall. Precision measures the accuracy of positive predictions (minimizing False Positives), while recall measures the ability to identify actual tumors (minimizing False Negatives). The F1 score, being the harmonic mean of precision and recall, provides a single, comprehensive metric that ensures the model captures most tumors without generating excessive false alarms. This balance is vital in a clinical setting where both missing a tumor and misclassifying normal scans can have significant consequences.

$$\text{F1 score} = 2 * \frac{\text{Precision}*\text{Recall}}{\text{Precision}+\text{Recall}} \tag{4}$$

$$\text{F1 score} = 2 * \frac{0.9626 * 0.9726}{0.9626 + 0.9726}$$

$$\text{F1 score} = 0.9676$$

The ROC curve, plotting True Positive Rate (correctly identified tumors) v/s False Positive Rate (normal brains flagged as abnormal), visualizes a model's ability to discriminate between classes. The AUC metric summarizes this curve's performance into a single value (0-1), with 0.98 in brain tumor classification indicating excellent performance in distinguishing tumors from healthy brains.

The proposed model is compared with existing deep learning architectures, namely EfficientNet-B0, ResNet-50, and Inception-v3, highlights its superior performance across all metrics. The Proposed Model achieves an accuracy of 96.5%, a precision of 96.26%, and a recall of 97.26%, outperforming its counterparts. EfficientNet-B0 follows closely with an accuracy of 95.0%, precision of 94.0%, and recall of 96.0%, reflecting its competitive yet slightly inferior performance. ResNet-50 and Inception-v3 demonstrate progressively lower results, with accuracies of 93.5% and 91.0%, precision values of 92.5% and 90.0%, and recalls of 94.0% and 92.0%, respectively. This comparison underscores the robustness of the Proposed Model, making it a highly effective solution for brain tumor identification in MRI scans as shown in figure 4.

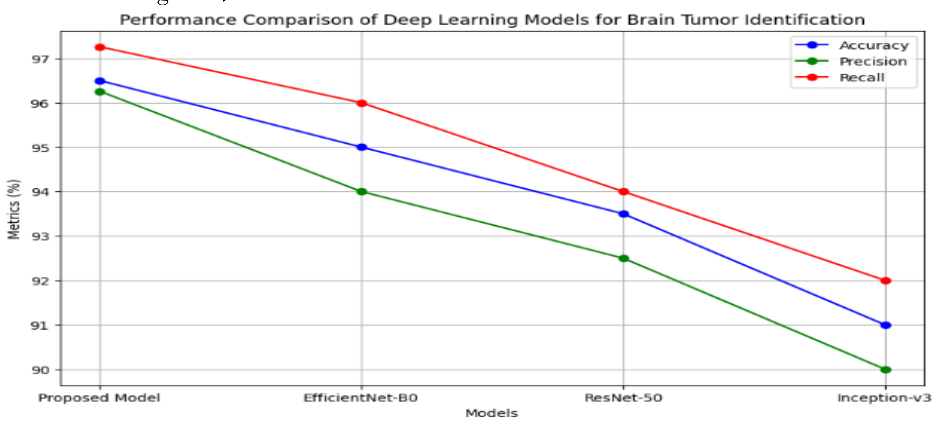

Figure 4: Comparison of the Proposed Model with existing Deep Learning Architectures

The CNN model demonstrates a better performance in brain tumor identification, achieving an accuracy of 96.5%, precision of 96.26%, recall of 97.26%, F1 score of 96.76%, and an AUC of 0.98. The confusion matrix underscores its reliability with only 20 false positives and 15 false negatives, ensuring accurate classification of normal and tumor MRI images. When compared to existing models like EfficientNet-B0, ResNet-50, and Inception-v3, the CNN model consistently outperforms them across all key metrics, highlighting its superior precision, recall, and overall effectiveness.

5. CONCLUSION AND FUTURE WORK

The proposed methodology highlights the significant efficacy of employing deep learning methodologies, specifically Convolutional Neural Networks (CNNs), coupled with morphological feature extraction techniques for brain tumor segmentation and classification in MRI images. The model's high accuracy with 96.5% illustrates its strong potential to aid medical professionals in the precise diagnosis and treatment planning of brain tumors, offering a valuable tool for enhancing patient outcomes. Moving forward, future research could focus on incorporating additional imaging modalities, such as PET or CT scans, to provide a more comprehensive analysis. Exploring more advanced neural network architectures, like transformers or hybrid models, could further enhance the model's performance. Moreover, developing techniques to improve the interpretability of the model's predictions is essential for gaining the trust of medical practitioners. Crucial to the practical application of this technology is clinical validation using real patient data, which will help to assess its robustness, reliability, and overall utility in real-world medical environments.

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