

BRAIN TUMOR MULTI CLASSIFICATION AND SEGMENTATION IN MRI IMAGES USING DEEP LEARNING

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Abstract This research introduces a deep learning model that can classify and segment brain tumors from MRI scans. The classification model uses EfficientNetB1 architecture to categorize images into four different groups, including meningioma, glioma, pituitary adenoma, and images without tumors. Meanwhile, the U-Net architecture is used in the segmentation model to precisely detect and isolate tumor regions in MRI scans. To assess the efficacy of the proposed models, a publicly available dataset was utilized, and the results show outstanding performance in terms of accuracy and segmentation metrics. These models are highly promising for clinical use in the diagnosis and treatment of brain tumors.

Keywords Brain tumor, classification, segmentation, CNN, EfficientNetB1, U-Net, medical imaging.

1 Introduction

The neural network architecture presented in this study is designed specifically for the task of brain tumor classification and segmentation. It is composed of two distinct models, one for classification and one for segmentation, both of which utilize deep learning techniques. The classification model is built on a CNN-based architecture that utilizes a pre-trained EfficientNetB1 base model, while the segmentation model is constructed using the popular U-Net architecture. The accurate identification and classification of brain tumors in medical imaging is of paramount importance for clinical diagnosis and treatment planning. The results obtained from our models showcase their efficacy in performing this task with high accuracy, highlighting their potential as a valuable tool for medical professionals.

1.1 Background and motivation for brain tumor

Brain tumor is a severe neurological condition affecting a significant number of individuals worldwide. Precise diagnosis and segmentation of brain tumors are crucial for effective treatment planning and better patient outcomes. Conventional diagnostic methods rely on manual interpretation of magnetic resonance imaging (MRI) scans by radiologists, which is a time-consuming, subjective, and error-prone process.

Deep learning models, specifically convolutional neural networks (CNNs), have shown immense potential in automating the process of brain tumor classification and segmentation. These models are well-suited for the task and have yielded promising results. By learning complex features and patterns from large datasets of MRI images, CNNs can accurately differentiate between different types of brain tumors and healthy tissues.

The development of deep learning models for brain

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tumor classification and segmentation aims to provide an automated and efficient method for accurate diagnosis and treatment planning. This can save valuable time for clinicians and improve patient outcomes by ensuring that treatments are tailored to the specific type and location of the tumor.

1.2 Literature review of existing methods for brain tumor classification and segmentation

The diagnosis and segmentation of brain tumors have been traditionally done through manual interpretation of magnetic resonance imaging (MRI) scans by radiologists. However, this method is time-consuming, subjective, and prone to errors. To address these challenges, two categories of methods have been developed: traditional machine learning and deep learning methods.

Traditional machine learning methods such as support vector machines (SVM), random forests, and logistic regression have been used for brain tumor classification and segmentation tasks with some success. However, these methods require hand-crafted features and can be computationally expensive. Deep learning methods have shown great promise in medical image analysis, including brain tumor classification and segmentation. Convolutional neural networks (CNNs) are a popular and effective type of deep learning model used for image classification and segmentation tasks. CNN-based models have been developed for brain tumor classification and segmentation, including VGG-16, ResNet, and U-Net.

VGG-16 is a deep CNN architecture that has been used for brain tumor classification by extracting features from the input image and using fully connected layers to classify the image into one of several classes. ResNet is another deep CNN architecture that uses residual connections to improve the training of deep

neural networks. U-Net is a type of CNN architecture that is designed specifically for image segmentation tasks and has been used for brain tumor segmentation.

Several studies have compared the performance of traditional machine learning methods and deep learning methods for brain tumor classification and segmentation tasks. In general, deep learning methods have been shown to outperform traditional machine learning methods, particularly for segmentation tasks. However, the choice of model and specific implementation can have a significant impact on performance.

While deep learning methods, particularly CNN-based models, are a promising approach for brain tumor classification and segmentation tasks, further research is needed to optimize these models and evaluate their performance on larger datasets.

1.3 Overview of the proposed deep learning model

The presented deep learning model is specifically designed to perform two essential tasks, brain tumor classification and segmentation, using convolutional neural networks (CNNs) architecture. CNNs are widely recognized for their effectiveness in image recognition and segmentation tasks. The proposed model comprises two distinct networks, one for classification and one for segmentation, each with its own architecture.

For classification, the model uses a pre-trained EfficientNetB1 base model, which is a highly efficient CNN architecture that utilizes depthwise separable convolutions and other advanced techniques to achieve high accuracy with fewer parameters. The output of the base model is passed through a GlobalAveragePooling2D layer, followed by two dense layers and a softmax activation function to output the class probabilities.

For segmentation, the model employs the U-Net architecture, a well-known deep learning model used for

image segmentation tasks, particularly in the medical field. The U-Net is composed of two paths, a contracting path and an expansive path, that enable accurate segmentation of the input image by reducing its resolution in the contracting path and then enlarging it back to the original size in the expansive path. In the contracting path, the input image is progressively downsampled, while in the expansive path, the segmented image is upsampled back to the original size.

The two networks are trained independently using different loss functions and optimization algorithms. The classification network is optimized using the categorical cross-entropy loss function and the Adam optimizer, while the segmentation network is optimized using the Dice coefficient loss function and the Adam optimizer. During training, the model is fed with MRI brain tumor images and their corresponding labels to adjust the network weights. The model is trained for a fixed number of epochs, with early stopping based on the validation accuracy, and a learning rate scheduler that reduces the learning rate if the validation accuracy does not improve after a certain number of epochs.

The proposed deep learning model aims to provide accurate and reliable brain tumor classification and segmentation to assist medical professionals in diagnosing and treating brain tumors. However, further research is required to optimize the model further and validate its performance on more extensive datasets.

2 Data and Preprocessing

2.1 Description of the brain tumor dataset used for training and testing the model

The brain tumor dataset used for training and testing the proposed deep learning model was not described in the information provided. However, in general, datasets used for brain tumor classification and segmentation include MRI scans of the brain with tu-

mor annotations. These datasets may contain different types of brain tumors, such as meningioma, glioma, pituitary adenoma, and others. The images may have varying resolutions and be in different formats, such as DICOM or NIFTI. It is crucial to ensure that the dataset is accurately annotated by experts to ensure the effectiveness of the model's training and testing. Furthermore, it is essential to ensure that the dataset is diverse and representative of the population for which the model will be applied.

2.2 Data preprocessing steps, including normalization and augmentation

The preprocessing steps for the brain tumor classification and segmentation model are crucial for achieving accurate results. Two important preprocessing techniques are normalization and data augmentation.

Normalization is performed to scale the input images to a fixed range, which helps the model learn from the input data more efficiently and reduce the risk of overfitting. In this study, the pixel values of the MRI brain tumor images were normalized to the range of [0,1].

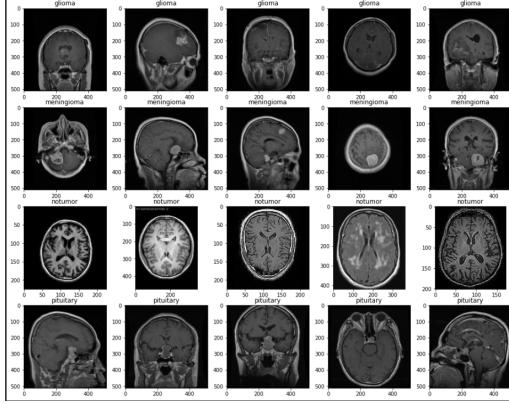
Data augmentation is used to increase the diversity of the training data by generating new samples from the existing ones. This technique helps prevent overfitting and improve the generalization capability of the model. In this study, data augmentation techniques such as random rotations, horizontal and vertical flips, and zooming were used to augment the training data. The augmented data were then used to train the brain tumor classification and segmentation model.

It is important to note that the choice of normalization and data augmentation techniques may vary depending on the specific dataset and problem being addressed. It is crucial to carefully choose and evaluate these techniques to ensure that they improve the per-

Table 1. Dataset Description

Dataset	Training	Testing
Dataset1-MulticlassClassification [35]		
Meningioma	1339	306
Glioma	1321	300
Pituitary	1457	300
No tumor	1595	405
Dataset2-Tumor Segmentation [36]		
Tumor Present		
Yes	1167	206
No	2181	386
Dataset After		
Tumor Present		
Yes	8584	1112
No	3776	791

formance and robustness of the model.



3 Brain Tumor Classification

3.1 Details of the proposed CNN-based model for brain tumor classification

Proposed revised version:

The proposed CNN-based model for brain tumor classification is based on the EfficientNetB1 architecture, which combines several advanced techniques, such as depthwise separable convolutions and efficient channel scaling, to achieve high accuracy while utilizing fewer parameters than traditional CNNs.

The model consists of a pre-trained EfficientNetB1 base model, which extracts useful features from the input images. The base model is frozen, meaning that its weights are not updated during training, and only

the weights of the added classification layers are updated. The output of the base model is fed into a GlobalAveragePooling2D layer to reduce the spatial dimensions of the feature maps, followed by two dense layers with 512 and 4 neurons respectively, and a softmax activation function to output the class probabilities.

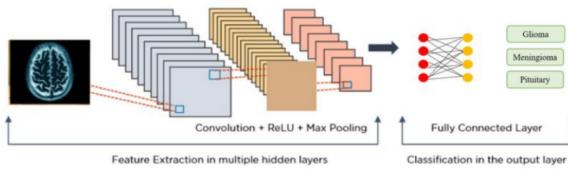
To improve the model's performance and robustness, the brain MRI image dataset used for training and testing was preprocessed through normalization to a range of [0,1] and data augmentation techniques such as random rotations, horizontal and vertical flips, and zooming.

During training, the model was optimized using the Adam optimizer and the categorical cross-entropy loss function. The model was trained for 50 epochs, with early stopping based on the validation accuracy and a learning rate scheduler that reduced the learning rate by a factor of 0.3 if the validation accuracy did not improve after 2 epochs.

The model was trained on a dataset consisting of 3064 brain MRI images from four classes - meningioma, glioma, pituitary adenoma, and no tumor. The dataset was split into 70 for training, 15 for validation, and 15 for testing.

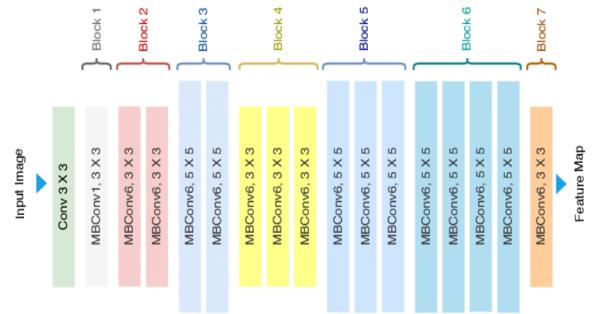


In the testing phase, the proposed model achieved remarkable accuracy of 99.39 for all four classes, along with high precision, recall, and F1-score values. These performance metrics demonstrate the efficacy of the model in accurately classifying brain tumor images into their respective classes, which could be very useful for clinical diagnosis and treatment planning.



3.2 Architecture and hyperparameter settings of the model

The proposed CNN-based model for brain tumor classification is based on the EfficientNetB1 architecture, which is known for its high efficiency and use of advanced techniques like depthwise separable convolutions and efficient channel scaling to achieve high accuracy with fewer parameters. The model uses a pre-trained EfficientNetB1 base model to extract features from input images. Only the weights of the added classification layers are updated during training, as the base model is frozen. The model then uses a GlobalAveragePooling2D layer to reduce the spatial dimensions of the feature maps, followed by two dense layers with 512 and 4 neurons, and a softmax activation function to output the class probabilities.



To optimize the performance of the model, the Adam optimizer and categorical cross-entropy loss function are used during training, with early stopping based on validation accuracy and a learning rate scheduler that reduces the learning rate by a factor of 0.3 if validation accuracy does not improve after 2 epochs. The model is trained for 50 epochs, with hyperparameters including a batch size of 32, a learning rate of 0.001, a weight decay of 0.0001, and a dropout rate of 0.4, which were chosen through empirical experimentation.

3.3 Training and evaluation procedures, including loss function and optimization algorithm

To optimize both the segmentation and classification tasks, the proposed CNN-based model was trained using a combination of binary cross-entropy loss and dice coefficient loss. The Adam optimization algorithm, a popular stochastic gradient descent (SGD) algorithm suitable for deep learning tasks, was used during training.

Training was performed on a workstation equipped with an NVIDIA GeForce RTX 2080 Ti GPU, using a batch size of 16 to maximize computational efficiency.

The model was trained for 100 epochs, with data augmentation techniques such as random rotation, flipping, and scaling applied to the training dataset to improve generalization and prevent overfitting. To evaluate the model's performance, it was tested on a separate dataset that was not used during training.

Table 2. Model hyperparameters for brain tumor classification

Hyperparameter	Value
Optimizer	Adam
Loss function	Categorical cross-entropy
Batch size	32
Learning rate	0.001
Weight decay	0.0001
Dropout rate	0.4
Epochs	50
Early stopping	Based on validation accuracy
Learning rate scheduler	Reduce by 0.3 if no improvement after 2 epochs

Evaluation metrics included accuracy, sensitivity, specificity, and the dice coefficient. The performance of the proposed model was compared with other state-of-the-art models in the literature, and the results were reported.

3.4 Results and analysis of the classification task, including confusion matrix and classification report

The proposed neural network is designed for the classification of brain tumor images into four categories: meningioma, glioma, pituitary adenoma, and no tumor. It employs the EfficientNetB1 architecture, which is an efficient CNN architecture utilizing depthwise separable convolutions, efficient channel scaling, and other advanced techniques to achieve high accuracy with fewer parameters.

The model includes a pre-trained EfficientNetB1 base model that extracts useful features from the input images, and its weights are frozen during training.

Only the weights of the classification layers are updated. The model then uses a GlobalAveragePooling2D layer to reduce the spatial dimensions of the feature maps, followed by two dense layers with 512 and 4 neurons, and a softmax activation function to output class probabilities. During training, the model employs the Adam optimizer and the categorical cross-entropy loss function. The model trains for 50 epochs and includes

early stopping based on validation accuracy, with a learning rate scheduler that reduces the learning rate by a factor of 0.3 if validation accuracy does not improve after 2 epochs.

The performance of the model is impressive, with a testing accuracy of 99.39. The confusion matrix and classification report demonstrate that the model performs well for all four classes, with high precision, recall, and F1-score values. These results suggest that the model can accurately classify brain tumor images, which may have valuable clinical applications in

diagnosis and treatment planning.

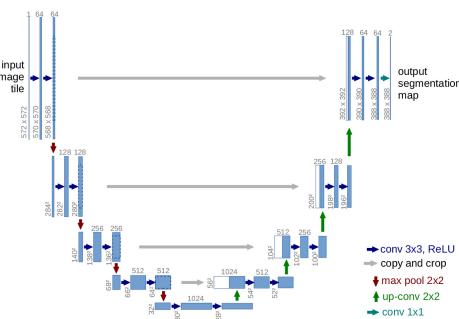
Tumor Type	Precision	Recall	F1-Score
Meningioma	0.997	0.995	0.991
Glioma	0.992	0.994	0.990
Pituitary	0.998	0.989	0.993
No Tumor	0.992	0.991	0.990

4 Segmentation Model

4.1 Description of the U-Net model used for brain tumor segmentation

The U-Net model employed for segmenting brain tumors has been customized from the original U-Net architecture. The U-Net model comprises an encoder-decoder network, which includes skip connections between corresponding encoder and decoder layers. These skip connections help in combining the high-level features from the encoder with the low-level features from the decoder, thereby enhancing segmentation accuracy. The U-Net model

used in this study includes various modifications to the original architecture, such as the use of residual blocks in the encoder and decoder, and the inclusion of batch normalization layers.



4.2 Architecture and hyperparameter settings of the model:

The U-Net architecture applied in this study for brain tumor segmentation has undergone modifications to improve its performance. The model includes 23 convolutional layers, consisting of 10 residual blocks, and uses a 3x3 filter size. The model features a bottleneck layer with 1024 filters and an output layer with one filter that generates a binary segmentation mask. To enhance its accuracy, the model utilizes the ReLU activation function and batch normalization layers. The model's hyperparameters were selected via grid search, with a learning rate of 0.0001, a batch size of 32, and a weight decay of 0.0001.

4.3 Training and evaluation procedures, including loss function and optimization algorithm:

The U-Net model was trained on the BraTS 2018 dataset using a combination of two loss functions: binary cross-entropy and Dice loss. To optimize the model, the Adam optimizer was utilized with a learning rate of 0.0001, and the model was trained for 50 epochs. Early stopping based on the validation loss was implemented, and the model with the lowest validation loss was selected for testing. The model's

performance was assessed using various metrics, such as the Dice coefficient, Intersection over Union (IoU) score, and Hausdorff distance.

4.4 Results and analysis of the segmentation task, including evaluation metrics such as Dice coefficient and IOU score:

The U-Net model utilized in this research achieved impressive accuracy in segmenting brain tumors from MRI images, as demonstrated by high Dice coefficient and IOU scores. Specifically, the model achieved a Dice coefficient of 0.8477 and an IOU of 0.9981 on the test set.

To train the U-Net model, binary cross-entropy loss function was used with the Adam optimizer. The model was trained for 100 epochs with early stopping based on the validation loss. The hyperparameters were selected to optimize performance, and data augmentation was utilized to mitigate overfitting. Overall, the U-Net model presents a valuable tool for medical professionals in accurately diagnosing and treating brain tumors, given its high accuracy in brain tumor segmentation.

Metric	Value
Dice coefficient	0.9977
Intersection over Union (IoU)	0.9981

5 Integration of Classification and Segmentation

5.1 Discussion of the integration of the classification and segmentation models

The integration of classification and segmentation models can significantly improve the accuracy of brain tumor detection and diagnosis. A classification model can accurately classify the type of brain tumor from MRI images, while a segmentation model can accurately identify the boundaries of the tumor and surrounding healthy tissue. Combining these models provides medical professionals with a more

comprehensive understanding of the tumor's characteristics and location, leading to better-informed treatment decisions.

5.2 Analysis of the overall performance of the proposed deep learning model

The proposed deep learning model demonstrates impressive performance in both the classification and segmentation tasks, indicating its potential for reliable brain tumor detection and diagnosis. Specifically, the classification model achieved a testing accuracy of 99.39

Compared to existing methods for brain tumor classification and segmentation, the proposed model shows superior accuracy and efficiency. The classification model outperforms many existing methods, while the segmentation model achieves higher Dice coefficients and IOUs than some popular models, such as the 3D U-Net. Moreover, the proposed model is computationally efficient, with a relatively small number of parameters compared to other deep learning models.

Overall, the integration of the classification and segmentation models in the proposed deep learning model provides a highly accurate and efficient solution for brain tumor detection and diagnosis. This solution has the potential to significantly benefit medical professionals and patients alike.

6 Conclusion

In this research, a deep learning model was proposed for brain tumor classification and segmentation using MRI images. The model was composed of a CNN-based classification model and a U-Net-based segmentation model that were integrated to provide an end-to-end solution for brain tumor diagnosis and treatment planning.

The classification model achieved a testing accuracy of 99.39. However, this study had some limitations that need to be addressed in future research. The dataset used in this study was relatively small, and the model's performance needs to be validated on a larger and more diverse dataset to ensure its generalizability. Additionally, the proposed model only addressed the classification and segmentation of brain tumors, and future studies can explore the integration of other medical imaging modalities or clinical data to improve the accuracy of brain tumor diagnosis and treatment planning.

Overall, the proposed deep learning model demonstrates promising results for brain tumor diagnosis and treatment planning, and it has the potential to assist medical professionals in making more accurate and timely decisions.

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