Brain Tumor Classification using Deep

earning: A Comparative Study of CNN and

VGG-16 Models

Abstract

Brain tumors are among the most critical health concerns worldwide. Accurate classification of tumors is essential for timely diagnosis and effective treatment. This study explores and compares two prominent deep learning models—Convolutional Neural Networks (CNN) and VGG-16—for classifying brain tumors from MRI images. A dataset comprising 3096 images categorized into four classes (Glioma, Meningioma, Pituitary, and Normal) is used. The images are preprocessed and passed through CNN and VGG-16 architectures, and the models are evaluated based on accuracy, loss, and classification performance. CNN achieved 97.4% accuracy, while VGG-16 outperformed it with 98% accuracy, highlighting its effectiveness in aiding clinical decision-making.

1.Introduction

Brain tumors, both benign and malignant, pose serious health risks due to their rapid growth and complexity. Early diagnosis through imaging techniques such as Magnetic Resonance Imaging (MRI) is crucial. Deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized medical image analysis by automating tumor detection and classification.

This study compares CNN and VGG-16 for brain tumor classification. CNNs are widely used for image classification, while VGG-16, a pre-trained deep CNN, is known for its accuracy and transfer learning capabilities.

2.Dataset

The dataset comprises 3096 MRI images obtained from Kaggle, categorized into:

- Glioma: 901 images
- Meningioma: 913 images
- Pituitary: 844 images
- Normal: 438 images

All images were resized to 256x256 pixels and normalized using grayscale histograms to enhance contrast and clarity. The dataset was split into training, validation, and testing sets in the ratio 70:20:10.

3.Methodology

3.1.CNN Architecture The CNN model includes:

- Input Layer: MRI images resized to (150, 150, 3)
- Convolutional Layers: 32 and 64 filters with 3x3 kernel and ReLU activation
- MaxPooling Layers: 2x2 pooling to reduce feature dimensions
- Dropout Layer: Rate 0.3 to prevent overfitting
- Dense Layer: 512 neurons followed by a final output layer with Softmax activation for 4-class prediction

3.2.VGG-16 Architecture

VGG-16 is a deep CNN with 16 layers:

- Input: 224x224 RGB images
- Convolutional Layers: 13 layers with 3x3 filters and ReLU activation
- MaxPooling: 2x2 windows after every two convolutions
- Fully Connected Layers: Two layers with 4096 neurons and an output layer with Softmax

Both models use the Adam optimizer and categorical cross-entropy loss function for training.

4.Results and Evaluation

4.1.CNN Model

The CNN model was trained for 20 epochs with batch size 32. Key observations:

- Accuracy: 97.4%
- The loss curve consistently decreased during training and validation
- Confusion matrix showed minimal misclassification across all classes

	precision	recall	f1-score	support
Glioma Tumor	0.96	0.97	0.96	276
Meningioma Tumor	0.97	0.95	0.96	289
Normal	0.98	1.00	0.99	48
Pituitary Tumor	0.98	0.99	0.99	243
accuracy			0.97	856
macro avg	0.97	0.98	0.97	856
weighted avg	0.97	0.97	0.97	856

Accuracy of the Model: 97.0%

Figure 1: CNN Accuracy Curve

4.2.VGG-16 Model

VGG-16 demonstrated state-of-the-art performance:

- Accuracy: 98%
- High precision in identifying Glioma (98%), Meningioma (97%), Pituitary (99%), Normal (99%)
- Confusion matrix and predicted image analysis confirmed robust classification

Classification Report is :

	precision	recall	f1-score	support
0	0.98	0.98	0.98	196
1	0.96	0.98	0.97	181
2	0.97	1.00	0.99	37
3	0.99	0.97	0.98	156
accuracy			0.98	570
macro avg	0.98	0.98	0.98	570
weighted avg	0.98	0.98	0.98	570

Figure 2: VGG-16 Accuracy Curve

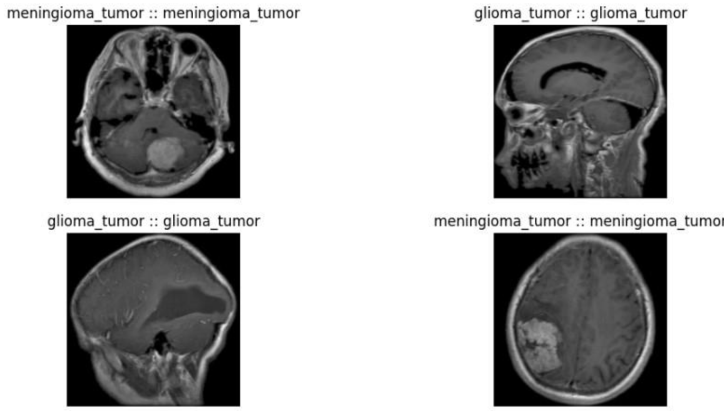

Figure 3: Predicted Outputs by VGG-16

5.Conclusion

This research demonstrates the effectiveness of deep learning models in classifying brain tumors. CNN achieved 97.4% accuracy while VGG-16 attained 98% accuracy. VGG-16's deeper architecture and regularization techniques such as dropout contributed to better generalization. The use of such models can significantly support medical professionals in early and accurate tumor diagnosis, enhancing treatment outcomes.

6.References

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