Deep Convolutional Neural Networks for Automated Brain Tumor Classification using MRI Imaging

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A R T I C L E I N F O

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A B S T R A C T

Brain tumor classification using MRI scans remains a critical challenge in medical diagnostics due to tumor heterogeneity and the complexity of accurate detection. Brain tumors are among the most aggressive and lethal types of cancer, making early diagnosis and treatment planning essential for improving patient prognosis. Deep learning aids detection, but robust clinical models are still needed. This study proposes a deep learning framework based on convolutional neural networks (CNNs) for the automated classification of brain tumors into four categories: no tumor, glioma, meningioma, and pituitary tumor. The model was evaluated using 7023 pre-labeled MRI images from one dataset [6] and compared its performance with existing state-of-the-art models. The proposed method achieved an accuracy of 91% in classification demonstrating its effectiveness and potential for clinical application. Evaluation metrics such as precision, recall and F1-Score demonstrated the model's robustness across tumor types, reinforcing its potential to support early and reliable brain tumor diagnosis.

1. Introduction

Brain tumors are among the most serious and life-threatening conditions affecting the central nervous system. They arise when abnormal cells grow uncontrollably within the brain or surrounding tissues. Depending on their type and location, brain tumors can cause severe neurological deficits, including seizures, cognitive impairments, motor dysfunction, and even death. The three most common types of primary brain tumors are gliomas, meningiomas, and pituitary tumors, each with distinct clinical behaviors and treatment approaches. Early and accurate diagnosis is essential for effective treatment planning and improving patient outcomes, nevertheless it remains a challenge due to the heterogeneity of tumors and overlapping imaging features.

According to recent global cancer statistics, brain and central nervous system tumors account for a significant number of cancer-related deaths, particularly due to their aggressive nature and late-stage diagnosis. The overall incidence of primary brain tumors is *21.42* per *100,000* inhabitants, with *5.42* per *100,000* in children aged 0 to 19. Regarding the mortality rate, approximately *18,330* people are estimated to die from brain tumors each year, including *10,170* men and *8,160* women. [2]

Magnetic Resonance Imaging (MRI) is the standard non-invasive technique used to visualize brain structures and detect abnormalities. However, manual interpretation of MRI scans is time-consuming, prone to observer variability or misdiagnose, and requires significant expertise. In recent years, deep learning, particularly convolutional neural networks (CNNs), has shown great promise in medical image analysis due to its ability to automatically learn and extract complex features from large datasets.

Despite these advances, the development of clinically robust and generalizable models remains an open challenge. Many deep learning approaches achieve high performance in controlled experimental settings but struggle to maintain accuracy across diverse patient populations and real-world clinical data. This highlights the need for frameworks that not only achieve high classification accuracy but also demonstrate stability and reliability across different tumor types and imaging conditions.

In this study, we propose a deep learning-based framework for the multi-class classification of brain tumors using MRI images. The dataset used contains 7,023 labeled MRI scans categorized into four classes: no tumor, glioma, meningioma, and pituitary tumor. We implemented and compared four different CNN models: two custom-built architectures, and two pre-trained models: VGG16 and MobileNetV2, to evaluate their performance in tumor classification tasks.

The training process included data preprocessing, normalization, and augmentation to improve model generalization. Performance was assessed using accuracy, precision, recall, F1-score and confusion matrices. This research aims to highlight the potential of CNN-based models as decision-support tools to assist radiologists in early and accurate tumor diagnosis, potentially improving clinical workflows and patient prognosis.

2. Related Work

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have become the dominant approach for medical image analysis, including brain tumor classification from MRI scans. CNNs have demonstrated the ability to automatically extract complex features from images, enabling improved diagnostic performance compared to traditional machine learning methods based on handcrafted features.

Several studies have explored CNN-based models for brain tumor classification. Havei et al. [3] (2017) proposed a two pathway CNN architecture capable of simultaneously capturing local and global features from brain MRI images, achieving notable accuracy in binary tumor classification tasks. Badža and Barjaktarović [4] (2020) employed a standard CNN to classify brain tumors into three major types — glioma, meningioma, and pituitary — reporting competitive results. Similarly, Swati et al. [5] (2019) leveraged transfer learning with a fine-tuned VGG16 model, demonstrating the advantages of pre-trained models when applied to medical imaging.

Transfer learning approaches, such as those utilizing VGG16, MobileNet, and ResNet, have shown promise by enabling models to cover faster and achieve better generalization, especially when labeled medical datasets are limited. However, many previous works focused primarily on binary classification tasks (tumor vs. no tumor) limiting the models' ability to generalize to multiclass classification involving different tumor types. Recently, segmentation-based methods - such as those employing U-Net architectures - have been integrated into some pipelines to isolate tumor regions before classifications [8]. While segmentation can improve classification performance by focusing on the relevant regions of interest, it also introduces additional complexity and potential error propagation if segmentation is imperfect.

Despite these advances in this field, challenges remain in achieving clinically robust classification across MRI datasets. Our work addresses these gaps by implementing and comparing multiple CNN-based architectures, including custom-designed networks and transfer learning models (VGG16 and MobileNetV2), directly on MRI images for multiclass brain tumor classification.

A summary of recent studies of brain tumor classification is presented in Table 1.

Author	Year	Method	Classes	Accuracy
Havaei et al.	2017	Two pathway CNN	Tumor / No tumor	96%
Badža & Barjaktarović	2020	Standard CNN	Glioma, Meningioma, Pituitary	97%
Swati et al.	2019	VGG16	Glioma, Meningioma, Pituitary	95%

Table 1. Summary of Recent CNN-Based Approaches for Brain Tumor Classification

3. Methodology and Resources

3.1 Dataset

The dataset used in this study consists of 7,023 pre-labeled Magnetic Resonance Imaging (MRI) scans collected from publicly available sources [6]. Images vary in contrast and quality, reflecting real-world clinical heterogeneity.

The dataset was split into training, validation, and testing sets following an approximate 80-10-10 split. 80% of the images in the training folder were used for model training, while 20% were reserved for validation through internal splitting. An independent test set was used for exclusive final evaluation.

3.2 Data Preprocessing

All images were resized to 150x150 pixels and normalized by scaling pixel values to the [0,1] range. Data augmentation techniques were applied during training to increase the effective size of the dataset and improve model generalization. These techniques included:

- Random rotations up to 10 degrees.
- Width and height shifts up to 20%.
- Zooming up to 30%.
- Horizontal flipping.
- Shear transformations up to 30%.

Grayscale and RGB versions of the images were both considered, depending on the model architecture requirements.

3.3 Model Architectures

Four different convolutional neural network (CNN) architectures were implemented and evaluated:

- Basic CNN: A custom-built CNN consisting of one convolutional layer followed by dense layers.
- Enhanced CNN: An extended version of the Basic CNN with additional convolutional layers.
- VGG16: Pre-trained VGG16 model with the fully connected top layers replaced and fine-tuned.
- MobileNetV2: Pre-trained MobileNetV2 model with global average pooling and dense layers adapted for the four-class output.

3.4 Training Procedure

All models were compiled using the Adam optimizer with a learning rate of 1e-5 and categorical cross-entropy as the loss function, given the multiclass nature of the problem.

The training process included continuous monitoring of accuracy and loss on both training and validation sets.

3.5 Evaluation Metrics

Model performance was assessed using several standard classification metrics:

- Accuracy
- Precision
- Recall
- F1-Score
- Confusion Matrix

4. Results

4.1 Training and Validation Performance

In order to improve model overall performance, several modifications were made to the training strategy, based on the base model. First we changed the loss function from binary cross-entropy to categorical cross-entropy in order to handle the multiclass classification task. Additionally, from the initial training strategy, we replaced the RMSprop optimizer with Adam, which provided a more adaptive optimization approach suitable for transfer learning scenarios.

A ReduceLROnPlateau callback was introduced to dynamically reduce the learning rate when the validation loss declined, which provided a more stable convergence during training. As well, for transfer learning models (VGG16 and MobileNetV2), the last 4 convolutional layers of the base networks were unfrozen and fine-tuned during training. This approach enabled the models to adapt more effectively while retaining the general features learned from ImageNet pretraining.

All models were trained for up to 50 epochs using early stopping and learning rate adjustment based on validation accuracy. The batch size was set to 32, Figures 1 and 2 illustrate the training and validation accuracy and loss curves for the VGG16 based model, which achieved the best validation performance among all evaluated architectures.

Figure 1. Training and Validation Accuracy for VGG16 model

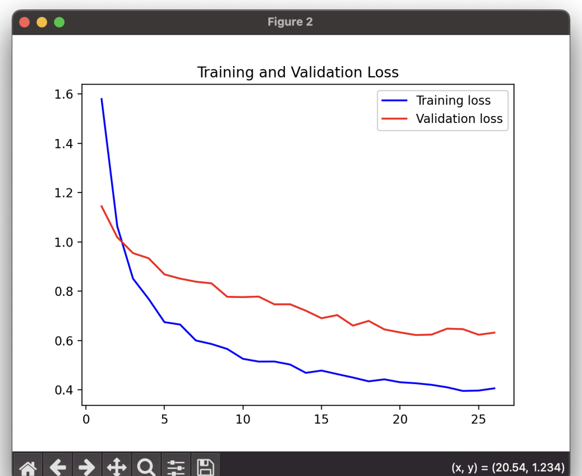

Figure 2. Training and Validation Loss for VGG16 model

4.2 Test Set Evaluation

Final model evaluation was performed on an independent test set consisting of MRI images not seen during training. Table 2 summarizes the performance of each model across key classification metrics.

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Basic CNN	56%	62%	56%	53%
Enhanced CNN	60%	64%	60%	57%
VGG16 (Transfer)	91%	91%	91%	90%
MobileNetV2 (Transfer)	79%	80%	79%	78%

Table 2. Performance Metrics on the Test Set

4.3 Confusion Matrices

Confusion matrices were generated for each model to visualize the classification performance across the four tumor categories. Figures 3 to 6 show the confusion matrices for Basic CNN, Enhanced CNN, VGG16, and MobileNetV2 models, respectively.

Figure 3. Confusion matrix for Basic CNN model

Figure 4. Confusion matrix for Enhanced CNN model

Figure 6. Confusion matrix for MobileNetV2 model

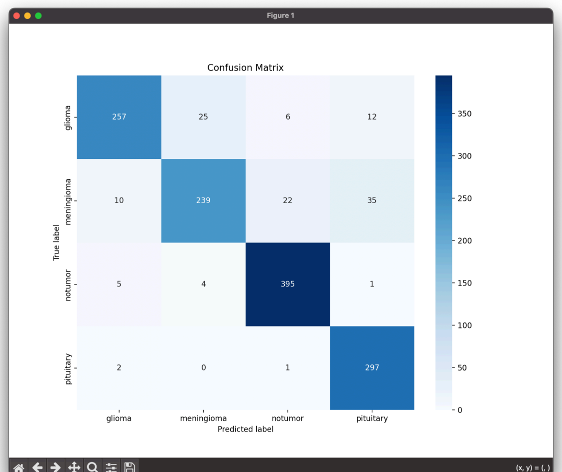

Figure 5. Confusion matrix for VGG16 model

4.4 Comparative Model Performance

A comparative bar chart was created to highlight the differences in test accuracy across models, as shown in Figure 7. The VGG16-based model demonstrated the highest classification accuracy, followed closely by the MobileNetV2-based model.

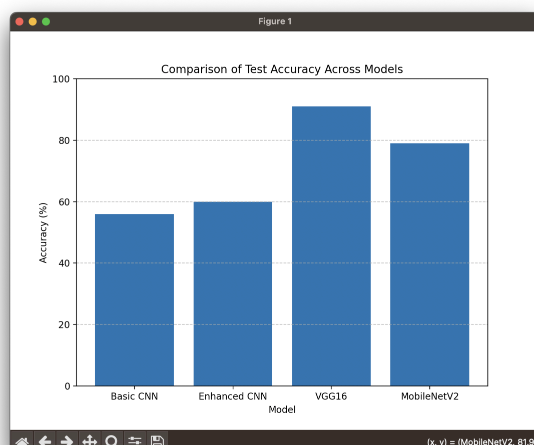

Figure 7. Comparison of Test Accuracy Across Models

4.5 Application Testing

The developed graphical user interface (GUI) application successfully predicted the tumor category for uploaded MRI images using the trained VGG16 and MobileNetV2 models. Example predictions and outputs are shown in Figure 8.

Both models correctly classified 4 out of 5 images, discrepancies occurred in one glioma MRI scan where each model predicted a different outcome.

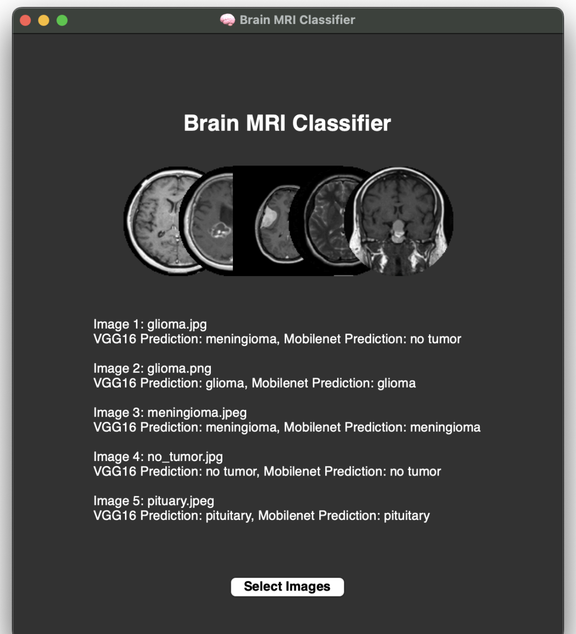

Figure 8. GUI Brain MRI Classifier

5. Discussion

This study evaluated four different CNN architectures for the classification of brain tumors using MRI images: a *Basic CNN*, an *Enhanced CNN*, and two transfer learning models *VGG16* and *MobileNetV2*. Among these, the VGG16-based model consistently outperformed, achieving the highest test accuracy, precision, recall, and F1-score across the dataset.

The ability to leverage features pre-trained on large and diverse datasets such as ImageNet, has a big impact on the performance of VGG16, this pre-training allowed the model to generalize better to the MRI data. MobileNetV2 also showed competitive results, confirming that lightweight architectures can be effective when computational resources are limited.

In contrast, the Basic CNN and Enhanced CNN models, though simpler and faster to train, underperformed compared to transfer learning approaches. This remarks the challenge of training deep learning models from scratch.

One limitation of this study is the exclusive focus on image classification without explicit tumor segmentation. Segmenting the regions of interest can enhance diagnostic accuracy and interpretability by focusing on the relevant structures (Ronneberger et al., 2015) [7]. Future work could integrate segmentation pipelines, such as U-Net architectures, to localize tumor areas before classification.

Overall, the proposed CNN-based framework demonstrates strong potential as a support tool for assisting radiologists in the early and accurate diagnosis of brain tumors. The refinement of such a framework, could enhance its clinical usability.

6. Conclusion

This study presents a deep learning-based framework for the automated classification of brain tumors into four categories using MRI images. By implementing and comparing multiple CNN architectures, including custom models and transfer learning approaches, the proposed system demonstrated strong performance, particularly when leveraging pre-trained networks.

The results highlight the effectiveness of convolutional neural networks in supporting early and accurate brain tumor diagnosis, which is critical for improving patients outcomes. Future work will focus on integrating segmentation techniques to localize tumor regions more precisely. By isolating the tumor area prior to classification, the model may identify relevant features, reducing background noise which will allow an increment in the diagnostic.

7. References

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