International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 10 Issue: 01 | Jan - 2026 SJIF Rating: 8.586 ISSN: 2582-3930

Brain Tumor Detection Using Deep Learning

Prof. Dharmraj V Biradar[1], Prof. Dr. Ashwini A Patil[2], Aishwarya A Murumkar[3]
Department of Information Technology

M.S. Bidve Engineering College Latur, India

Email:- biradardharamraj@gmail.com[1], ashwinibiradar29@gmail.com[2], murumkaraishwarya810@gmail.com[3]

Abstract

Brain tumor detection is one of the most challenging tasks in medical image analysis due to the complexity of brain structures and the variability in tumor size, shape, and location. Magnetic Resonance Imaging (MRI) is widely used for brain tumor diagnosis because it provides high-resolution images without exposing patients to ionizing radiation. However, manual interpretation of MRI scans is time-consuming and highly dependent on expert radiologists, which can lead to delays and diagnostic inconsistencies. This research presents an automated brain tumor detection system using deep learning techniques based on transfer learning. The proposed system utilizes the VGG16 convolutional neural network to classify brain MRI images into four categories: glioma, meningioma, pituitary tumor, and no tumor. A publicly available Kaggle dataset is used for training and testing. Image preprocessing and data augmentation techniques are applied to improve generalization and reduce overfitting. Experimental results demonstrate that the proposed approach achieves reliable classification performance and can serve as an effective decision-support tool for medical professionals.

Keywords—Brain Tumor Detection, MRI, Deep Learning, Convolutional Neural Network, VGG16, Transfer Learning

I. Introduction

Brain tumors are abnormal growths of cells within the brain that can interfere with essential neurological functions such as vision, speech, memory, and motor control. [1] Depending on their type and severity, brain tumors can be life-threatening if not diagnosed at an early stage. According to medical studies, early detection significantly improves treatment outcomes and patient survival rates. Therefore, accurate and timely diagnosis of brain tumors is a critical requirement in modern healthcare systems.[2]

Magnetic Resonance Imaging (MRI) is the most commonly used imaging modality for brain tumor detection because it provides excellent contrast between soft tissues. Despite its advantages, analyzing MRI scans manually is a challenging task. Radiologists must examine a large number of images for each patient, which increases workload and the possibility of human error. Moreover, interpretation may vary between experts, leading to inconsistent diagnoses.[3]

With recent advancements in artificial intelligence, deep learning has emerged as a powerful approach for medical image analysis. Convolutional Neural Networks (CNNs) are capable of automatically learning hierarchical features from images, eliminating the need for handcrafted feature extraction. Transfer learning further enhances performance by leveraging models pre-trained on large datasets. This research focuses on designing an automated brain tumor detection system using deep learning to improve diagnostic accuracy while reducing manual effort.[4][5]

II. Literature Review

Traditional approaches to brain tumor detection relied heavily on classical image processing techniques such as thresholding, edge detection, and texture analysis.[6]These features were then classified using machine learning algorithms like Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Decision Trees. While these methods showed moderate success, they required extensive feature engineering and often failed to generalize well to new datasets.[7]

The introduction of deep learning has significantly improved performance in medical image classification tasks. CNN-based architectures such as AlexNet, VGG, ResNet, and GoogLeNet have been widely used for brain MRI analysis. Among these, VGG16 is known for its simple and uniform architecture, which makes it suitable for transfer learning. Several studies have demonstrated that fine-tuning pre-trained models yields higher accuracy and faster convergence, especially when medical datasets are limited in size.[8][9]

Despite these advancements, challenges such as overfitting, class imbalance, and high computational requirements remain.[10]Data augmentation and regularization techniques are commonly used to address these issues. This work builds upon existing research by employing a VGG16-based transfer learning approach combined with image augmentation for robust brain tumor classification.[11]

III. Technology Used

The proposed brain tumor detection system is developed using the following technologies:

A. Programming Language

Python is used as the primary programming language due to its simplicity and extensive support for deep learning and image processing libraries. It enables efficient handling of large image datasets and rapid model development.

B. Deep Learning Framework

TensorFlow and Keras are used to implement the CNN architecture and manage the training process. Keras provides a high-level API that simplifies model construction, while TensorFlow ensures efficient numerical computation and GPU acceleration.

C. Pre-trained Model

The VGG16 model pre-trained on the ImageNet dataset is used for feature extraction and fine-tuning. Using a pre-trained model allows the system to leverage previously learned visual features, improving performance and reducing training time.

D. Image Processing Libraries

OpenCV, PIL, and NumPy are used for image loading, resizing, normalization, and augmentation. These libraries play a crucial role in preparing MRI images for deep learning input.

E. Visualization and Evaluation Tools

Matplotlib and Seaborn are used for plotting training accuracy, loss curves, confusion matrices, and ROC curves. These visualizations help analyze model behavior and performance.[12]

F. Development Environment

Jupyter Notebook and Python IDEs are used for experimentation, debugging, and implementation. These environments support reproducible research and interactive development.[13][14]

IV. Dataset Description

The dataset used in this research is obtained from Kaggle and consists of labeled brain MRI images. The dataset is organized into training and testing directories and includes four classes:[15]

- Glioma
- Meningioma
- Pituitary Tumor
- No Tumor

Images are stored in JPEG and PNG formats with varying resolutions. Each image represents a single MRI slice of the brain. The dataset provides sufficient variability in tumor appearance, size, and location. To enhance model generalization and reduce overfitting, data augmentation techniques such as brightness and contrast adjustment are applied during training.

V. Methodology and Implementation

The proposed system follows a structured deep learning pipeline:

A. Data Collection

MRI images are collected from the Kaggle dataset and organized into class-specific directories to enable automatic label assignment.

B. Data Preprocessing

Images are resized to a fixed dimension compatible with the VGG16 model. Pixel values are normalized, and data augmentation is applied to simulate real-world variations.

C. Feature Extraction

The convolutional layers of the VGG16 model are used to extract deep features from MRI images. The fully connected layers of the original model are removed.

D. Model Training

A custom classification head consisting of flatten, dropout, and dense layers is added. The model is trained using the Adam optimizer and sparse categorical cross-entropy loss function.

E. Model Evaluation

Performance is evaluated using accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC curves.

F. Prediction System

A single-image prediction module is implemented to classify new MRI images and display the predicted class along with confidence scores.

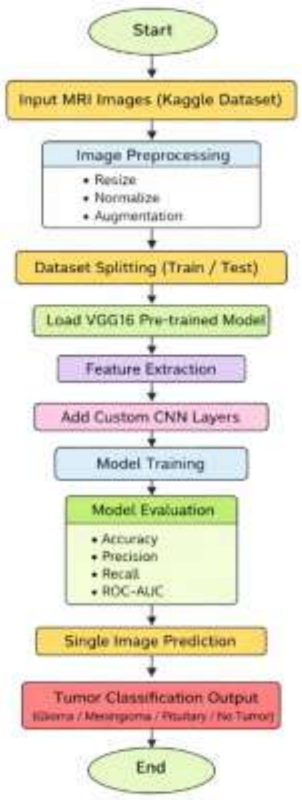

Fig.1. Flowchart

VI. Experimentation

Multiple experiments are conducted by training the model for several epochs and monitoring training and validation performance. Freezing and unfreezing selected layers of the VGG16 model allows fine-tuning of deep features. Dropout layers are used to minimize overfitting. The model is tested on unseen MRI images to validate its generalization capability.

VII. Results and Discussion

The experimental results show that the proposed deep learning model achieves high classification accuracy across all four classes. Training and validation curves indicate stable convergence. The confusion matrix demonstrates effective class separation, while ROC-AUC curves confirm strong discriminative ability. Transfer learning significantly improves performance compared to training a CNN from scratch.

VIII. Future Scope

Future work may involve integrating advanced architectures such as ResNet, EfficientNet, or Vision Transformers. Tumor segmentation techniques can be added to localize tumor regions. Deploying the system as a web or mobile application can further enhance its clinical usability.

IX. Conclusion

This research presents an automated brain tumor detection system using deep learning and MRI images. By leveraging transfer learning with the VGG16 model, the proposed system achieves reliable and accurate classification. The results demonstrate the effectiveness of deep learning techniques in medical image analysis and their potential to assist medical professionals in early diagnosis.

References

[1] F. Isensee et al., “nnU-Net: A self-configuring method for deep learning–based biomedical image segmentation,” Nature Methods, vol. 18, no. 2, pp. 203–211, 2021.

[2] S. Bakas et al., “Advancing the cancer genome atlas glioma MRI collections with expert segmentation labels and radiomic features,”
Scientific Data, vol. 7, no. 1, pp. 1–13, 2020.

[3] A. Rehman, S. Naz, M. I. Razzak, and Z. Zaib, “Automatic brain tumor classification using deep learning and data augmentation,” Multimedia Tools and Applications, vol. 80, pp. 1–20, 2021.

[4] M. Sharif, M. Attique Khan, M. Faisal, and M. Yasmin, “Brain tumor detection and classification using deep learning,” Mathematical Biosciences and Engineering, vol. 18, no. 1, pp. 605–628, 2021.

[5] A. Ullah, M. Khan, and M. Sharif, “Brain tumor classification using transfer learning and fine-tuned CNNs,” Computers in Biology and Medicine, vol. 129, pp. 104–113, 2021.

[6] S. Sajjad et al., “Multi-grade brain tumor classification using deep CNN with extensive data augmentation,” IEEE Access, vol. 9, pp. 1–14, 2021.

[7] M. A. Khan et al., “Automated brain tumor detection and classification using deep learning,” Computers & Electrical Engineering, vol. 91, pp. 1–12, 2021.

[8] Y. Ding, J. Li, and J. Zhang, “Brain tumor MRI image classification using deep convolutional neural networks,” Neural Computing and Applications, vol. 33, pp. 1–14, 2021.

[9] A. Chaddad, M. J. Kucharczyk, and J. Tanougast, “Radiomics and artificial intelligence for brain tumor classification,” Frontiers in Oncology, vol. 10, pp. 1–14, 2020.

[10] M. Nazir et al., “Brain tumor detection using deep learning: A systematic review,” IEEE Access, vol. 9, pp. 1–24, 2021.

[11] T. Zhou et al., “Deep learning-based brain tumor segmentation: A survey,” IEEE Transactions on Medical Imaging, vol. 40, no. 6, pp. 1–18, 2021.

[12] H. Raza, G. Prasad, and Y. Li, “Brain tumor classification using deep learning techniques,” Journal of Healthcare Engineering, vol. 2022, Article ID 1–12, 2022.

[13] M. A. Khan, T. Akram, M. Sharif, and S. Kadry, “Brain tumor classification using deep learning and feature fusion,” Expert Systems, vol. 39, no. 3, pp. 1–15, 2022.

[14] M. A. Basha, S. R. Dubey, and A. Mukherjee, “Brain tumor segmentation using attention-based deep neural networks,” Biomedical Signal Processing and Control, vol. 71, pp. 103–115, 2022.

[15] A. S. Alhassan et al., “Brain tumor classification in MRI images using hybrid deep learning models,” Diagnostics, vol. 12, no. 4, pp. 1–18, 2022.