Brain Tumor Detection and Classification Using Deep Learning

Vaibhavi Ghorpade[1], Sanika Patekar[2], Sanika Satre[3], Gauri Wakchaure[4], Prof. Dr. Sachine Bere[5], Mr. A. M. Suryawanshi[6]

[1,2,3,4]*Students, Department of Computer Engineering, Dattakala Group of Institutions Faculty of Engineering, Pune, Maharashtra, India.*

[5]*Guide, Department of Computer Engineering, Dattakala Group of Institutions Faculty of Engineering, Pune, Maharashtra, India.*

[6]*Co-Guide, Department of Computer Engineering, Dattakala Group of Institutions Faculty of Engineering, Pune, Maharashtra, India.*

***Abstract*—This paper introduces a deep learning-based approach for detecting brain tumors through transfer learning and MRI images. To categorize MRI scans into four groups—glioma, meningioma, pituitary tumor, and no tumor—a pre-trained VGG16 model is refined. To enhance model generalization, images are preprocessed using techniques like scaling, normalization, and augmentation. With 97.45% accuracy and over 96% precision, recall, and F1-score, the system performs well. The usefulness of VGG16 for medical image categorization is demonstrated by the model's considerable improvement over a baseline CNN. The findings point to a great deal of promise for clinical integration, providing radiologists with a quick and trustworthy way to get a second opinion. This method reduces human error, improves diagnostic efficiency, and demonstrates the usefulness of transfer learning in healthcare applications.**

***Index Terms*—Brain Tumor Detection, Magnetic Resonance Imaging (MRI), Convolutional Neural Network (CNN), Deep Learning, Transfer Learning, VGG16, Medical Image Analysis, Image Preprocessing, Data Augmentation, Automated Diagnosis.**

I. INTRODUCTION

Brain tumor detection is critical to patient survival, yet image complexity, or inexperience. In addition to this, variation in the size, type, and location of tumors cre- ates further diagnostic difficulties. Conventional machine 2 6
manual MRI interpretation is time-consuming and error-
prone. Deep learning, particularly Convolutional Neural Networks (CNNs), has emerged as a powerful tool in medical imaging. However, training CNNs from scratch requires large datasets, often unavailable in healthcare. Transfer learning solves this by adapting pre-trained mod- els like VGG16 to new tasks. This study implements a VGG16-based model trained on MRI images to clas- sify four tumor types. Images are preprocessed and aug-
mented to increase accuracy and generalization. The objec- tive is to develop an automated diagnostic tool that assists radiologists in making faster, more accurate decisions. By reducing manual workload and improving classification reliability, the proposed system supports better clinical outcomes.

II. PROBLEM STATEMENT

Brain tumors, one of the most serious neurological dis- eases, require rapid and precise diagnosis to maximize treatment success. Nonetheless, manual MRI scan analy- sis is extremely time-consuming and may lead to subjec- tive diagnostic flaws as a result of fatigue of radiologists, learning methods tend to be prone to manual feature ex- traction and lack generalizability across diverse datasets. As a result, there is a high need for fast, accurate, and au- tomated systems that can efficiently identify brain tumors from MRI scans. This work aims at using deep learning methods, specifically VGG16-based transfer learning, to address these challenges.The scope of the research also includes applying preprocessing techniques, such as im- age normalization, resizing, and data augmentation, to optimize the model's performance and improve its gener- alizability across different datasets. The model's perfor- mance will be assessed using common evaluation metrics, including accuracy, sensitivity, specificity, and F1-score. Ultimately, the research aims to create a robust, reliable, and efficient tool that can assist healthcare professionals in detecting brain tumors earlier, improving patient out- comes, and reducing the burden on medical practitioners.

III. LITERATURE REVIEW

Deep learning's use in medical imaging has expanded quickly, particularly in the use of MRI scans for brain
2
tumordiagnosis. CNN-based models have been investi- gated by many researchers for tumor classification. Al- though Miah et al. (2021) only used a rudimentary CNN for binary classification, they were able to obtain 99.52ac- curacy. The 5-layer CNN created by Nayan et al. (2022) outperformed YOLOv5, although it was computationally complex. Although it required a significant amount of re- sources, Zahoor et al. (2022) achieved 99.56ensemble clas- sifiers with enhanced features. Although EfficientNetB0 was used with transfer learning by Balaji et al. (2021), explainability was lacking. Yang et al. (2021) encountered poor generalization while using VGG19 for short datasets. These investigations demonstrate increasing success, but they also point to difficulties with precision, speed, and clinical application. In order to fill these gaps, our study uses VGG16.

1. Miah et al. (2021) implemented a CNN with Soft- max for binary tumor classification, achieving 99.52Gap: Focused only on binary classification; lacks tumor type distinction.
2. Nayan et al. (2022) built a 5-layer CNN outperform- ing YOLOv5. Gap: High complexity; lacks real-time diag- nostic integration.
3. Zahoor et al. (2022) used deep ensemble learning and boosted features with 99.56Gap: High memory usage and training time.
4. Balaji et al. (2021) applied EfficientNetB0 with ResNet50 via transfer learning. Gap: Absence of explain- ability for clinical use.
5. Raza et al. (2020) used Mask R-CNN for segmen- tation and classification. Gap: Inference speed is low, limiting real-time applications.
6. Yang et al. (2021) used VGG19 on small datasets with high sensitivity. Gap: Poor generalization on diverse data sources.
7. Sharma et al. (2021) combined CNN and SVM for classification. Gap: Manual feature extraction reduced flexibility and scalability.
8. Patel et al. (2023) proposed a 3D CNN for volumet- ric brain scans. Gap: Long training time and high GPU requirements.
9. Ali et al. (2023) used lightweight CNN with ROI extraction to improve speed. Gap: Lower classification accuracy compared to deeper models.
10. Khan et al. (2024) deployed a multi-scale CNN for fine-grained classification. Gap: Lacks integration of clini- cal metadata and explainability.

IV. METHODOLOGY

Dataset

MRI images were sourced from a publicly available dataset consisting of four categories: glioma, meningioma, pituitary tumor, and no tumor. The dataset was divided into training and testing sets for model development and evaluation.

Preprocessing

The images were preprocessed as follows:

- Resized to 128 ×128 pixels.
- Pixel values normalized to the range 0–1.
- Data augmentation applied to enhance model gener- alization, including:
  - Random rotation
  - Zoom
  - Width and height shift
  - Shear transformation

Model Architecture

A transfer learning approach was used with the VGG16 model pre-trained on ImageNet, with the top classification layers removed. The custom layers added were:

- Flatten layer
- Dropout layer (30%) to prevent overfitting
- Dense layer with 128 units and ReLU activation
- Dropout layer (20%)

- Output Dense layer with Softmax activation for 4- class classification

Training Strategy

The model was trained using the following configuration:

- Optimizer: Adam with a learning rate of 0.0001
- Loss function: Sparse categorical crossentropy
- Epochs: 20
- Batch size: 20
- Callbacks used to improve training:

– EarlyStopping to halt training when validation performance stopped improving

– ReduceLROnPlateau to reduce learning rate on plateau

– ModelCheckpoint to save the best model

Diagram

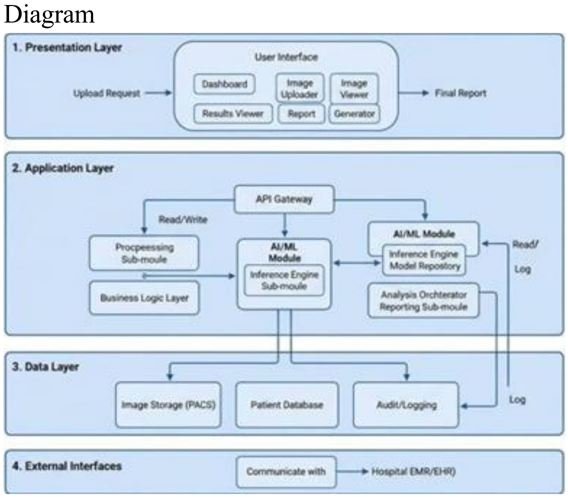

Figure 1 System Architecture

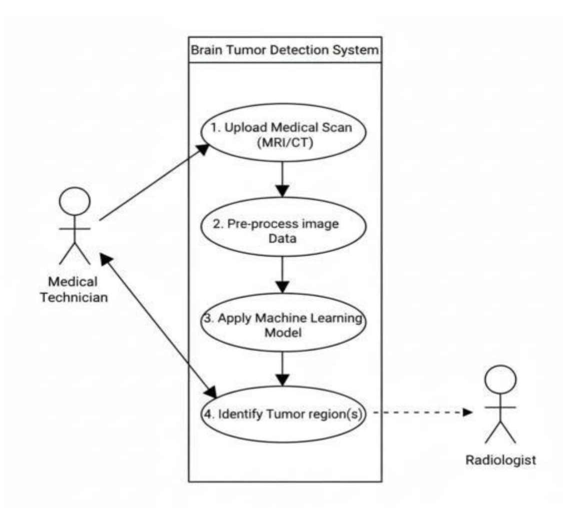

Figure 2 Use Case

V. CONCLUSION AND FUTURE SCOPE

This study effectively illustrates a method for classifying brain tumors using deep learning and MRI data that is both accurate and efficient. The system outperformed a baseline CNN model built from scratch by achieving a classification accuracy of 97.45using transfer learning through a pre-trained VGG16 model. Improving model robustness and generalization required the inclusion of appropriate picture preprocessing and data augmentation.

The finished model provides radiologists and other med- ical professionals with a trustworthy assistance tool by classifying tumors into four categories: glioma, menin- gioma, pituitary, and no tumor. The system could be im- proved in a number of ways if more time and money were available. Initially, segmentation models such as U-Net or Mask R-CNN could be used to locate the tumor in the MRI image in addition to classifying it. Second, the model's predictions could be made more transparent and clinically interpretable by including explainable AI approaches like Grad-CAM. Third, to increase diagnostic precision, the model might be extended to incorporate multi-modal in- puts such as genetic information, symptoms, or patient history. Lastly, a full deployment pipeline may be created to implement this system in clinics and hospitals, either as a web based tool or as a desktop program. All things considered, this project shows the effectiveness of deep learning and transfer learning in medical picture analysis and establishes a strong basis for further development in the direction of creating a clinical-grade brain tumor detection system.

REFERENCES

[1] Miah et al., "CNN-based Brain Tumor Detection," IEEE Access, 2021.

[2] Nayan et al., "Deep Learning for Brain MRI Classifica-

[3] tion," Neurocomputing, 2022.

[4] Zahoor et al., "Ensemble Learning for Brain Tumors,"

[5] Computers in Biology and Medicine, 2022.

— Balaji et al., "Transfer Learning in MRI Tumor Detec-

[6] tion," IJCNN, 2021.

[7] Raza et al., "Mask R-CNN for Tumor

Segmentation,”
[8] IEEE Trans. Med. Imaging, 2020.
[9] Yang et al., “Tumor Classification Using VGG19,”
[10] Computer Methods and Programs in Biomedicine, 2021.
[11] Sharma et al., “CNN-SVM Hybrid Approach,” Journal of Healthcare Engineering, 2021.
[12] Patel et al., “3D CNN for Volumetric Brain Tumor
[13] Detection,” NeuroImage, 2023.
[14] Ali et al., “ROI-based Brain Tumor Detection,” ICIP, 2023.
[15] Khan et al., “Multi-scale CNN for Brain MRI,” Journal of Biomedical Informatics,
[16] S. Pereira, A. Pinto, V. Alves, and C. A. Silva, “Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images,” IEEE Trans. Med. Imaging, vol. 35, no. 5, pp. 1240–1251, May 2016.
[17] J. Cheng et al., “Enhanced Performance of Brain Tumor Classification via Tumor Region Augmentation and Partition,” PLOS One, vol. 10, no. 10, e0140381, 2015.
[18] L. A. Tabassian and M. A. Khandoker, “Brain Tumor Classification Using Deep Features from Pre trained Models: Transfer Learning Approach,” Computers in Biology and Medicine, vol. 139, 104990, 2021.
[19] A. Rehman et al., “Classification of Brain Tumor MRI Images Using CNN with Data Augmentation and Deep Features,” Biomedical Signal Processing and Control, vol. 71, 103076, 2022.