

# BRAIN TUMOR DETECTION USING CONVOLUTIONAL NEURAL NETWORK

Tanzeem Akhtar  
2202160100111  
Dept. Of Computer Science  
and Engineering  
IIMT College Of Engineering  
AKTU

Majid Hussain  
2202160100064  
Dept. Of Computer  
Science and Engineering  
IIMT College Of Engineering  
AKTU

Arquam Imteyaz  
2202160100033  
Dept. Of Computer  
Science and Engineering  
IIMT College Of Engineering  
AKTU

Danish Mustaque  
2202160100035  
Dept. Of Computer  
Science and Engineering  
IIMT College Of Engineering  
AKTU

MS. Neeraj  
Assistant Professor  
Dept. Of Computer Science and Engineering

## 1. ABSTRACT

With the rapid advancement of medical imaging technologies, the volume of brain MRI data has significantly increased, making manual analysis by radiologists both time-consuming and prone to human error. Early and accurate detection of brain tumors is critical for effective diagnosis, treatment planning, and improving patient survival rates. This research presents an automated approach for brain tumor detection using Convolutional Neural Networks (CNNs), a class of deep learning models known for their superior performance in image analysis tasks.

The proposed system utilizes CNN architectures to automatically learn and extract complex spatial features from MRI images, enabling efficient differentiation between normal and tumor-affected brain tissues. The methodology involves preprocessing MRI scans, followed by feature extraction through multiple convolutional and pooling layers, and finally classification using fully connected layers. This eliminates the need for manual feature engineering, thereby improving efficiency and scalability.

The model is trained and evaluated on benchmark MRI datasets to ensure robustness and generalization. Experimental results demonstrate high accuracy, precision, and consistency in tumor detection and classification, highlighting the effectiveness of the proposed method. Compared to traditional diagnostic approaches, the automated system significantly reduces analysis time and enhances reliability.

Furthermore, this research emphasizes the potential of integrating artificial intelligence in healthcare systems to support radiologists in decision-making processes. The developed model can serve as a supportive tool for early diagnosis, reducing workload and minimizing diagnostic errors. Overall, the study contributes to the advancement of intelligent medical imaging systems and showcases the applicability of deep learning techniques in addressing

critical healthcare challenges such as brain tumor detection.

## 2. KEYWORDS

Brain Tumor Detection, Convolutional Neural Network, Deep Learning, Medical Image Processing, MRI Analysis, Artificial Intelligence, Computer-Aided Diagnosis

## 3. INTRODUCTION

The rapid growth of medical imaging technologies has significantly increased the availability of brain MRI data in healthcare systems. Brain tumors are among the most severe neurological disorders, and their early detection is essential for improving patient survival rates. However, manual examination of MRI scans by medical experts is complex, time-intensive, and prone to diagnostic inconsistencies.

Artificial Intelligence (AI) and Machine Learning (ML) techniques have emerged as effective solutions for automated medical image analysis. In particular, deep learning models such as Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in image classification and pattern recognition tasks. CNNs are capable of automatically extracting hierarchical features from MRI images, eliminating the need for handcrafted feature engineering and enabling the modeling of complex spatial and structural patterns in medical imaging data. Most existing brain tumor diagnosis systems rely heavily on manual inspection, which becomes increasingly challenging with the growing volume of medical imaging data. Automated systems are therefore required not only to detect tumors accurately but also to assist medical professionals with reliable and consistent interpretation. Traditional image processing techniques alone are often insufficient, particularly when handling complex tumor shapes, heterogeneous textures, and intensity variations

## 4. LITERATURE REVIEW

Brain tumor detection is a critical area in medical imaging that focuses on the early and accurate identification of tumors using MRI scans. Traditional methods used image processing techniques such as thresholding, segmentation, and clustering, but these often lacked accuracy and required manual feature extraction. Machine learning approaches, including Support Vector Machines (SVM) and Artificial Neural Networks (ANN), improved detection by classifying tumors based on extracted features. Recently, deep learning models, especially Convolutional Neural Networks (CNNs) and U-Net architectures, have significantly enhanced performance by automatically learning features from MRI images. These methods provide higher accuracy, better segmentation, and reduced human intervention. Public datasets like BRATS have supported the development and evaluation of these models. Although deep learning offers promising results, challenges such as limited data, model interpretability, and clinical implementation remain. Overall, modern AI-based techniques have greatly advanced brain tumor detection and continue to improve diagnostic efficiency. Recent literature highlights the growing use of deep learning techniques, especially Convolutional Neural Networks (CNNs), for brain tumor detection and segmentation. CNN-based models such as AlexNet, ResNet, VGG, and U-Net have demonstrated superior performance by automatically extracting complex features from MRI scans. U-Net, in particular, has become widely used for precise tumor segmentation due to its strong localization capabilities. Transfer learning and hybrid models combining CNN with traditional classifiers have further improved accuracy, especially when working with limited datasets. Public datasets such as BRATS have become standard benchmarks for evaluating these approaches. Most recent studies report high accuracy, sensitivity, and Dice scores using deep learning models. Despite these advancements, challenges remain in terms of data scarcity, model interpretability, and clinical deployment. Overall, the literature indicates a clear shift from traditional image processing toward advanced deep learning

## 5. METHODOLOGY

### 5.1 Dataset Description

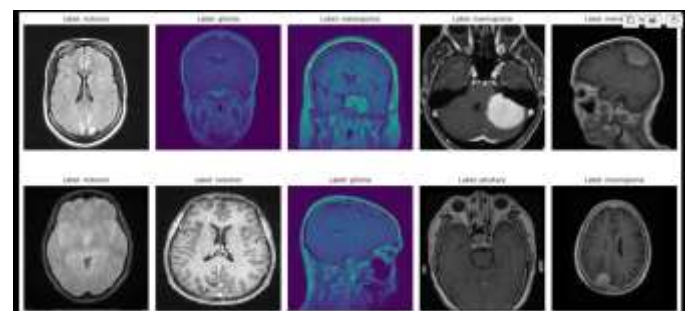
The project employs the PaySim dataset on Kaggle, which simulates more than 6 million brain tumor

MRI Images. It has types no tumor, pituitary and meningioma

### 5.2 Data Preprocessing

Data processing is an essential step in brain tumor detection to improve the quality and consistency of MRI images before model training. First, the Kaggle dataset images were collected and organized according to their class labels, such as tumor and non-tumor categories or specific tumor types. All images were resized to a fixed dimension to maintain uniformity and ensure compatibility with the deep learning model.

Image normalization was then applied to scale pixel intensity values, which helps improve model convergence and computational efficiency. Noise reduction and image enhancement techniques were used where necessary to improve image clarity. To increase the size and diversity of the dataset, data augmentation methods such as rotation, flipping, zooming, and shifting were performed. These techniques help reduce overfitting and improve model generalization. After preprocessing, the dataset was split into training, validation, and testing sets to support effective model training and accurate performance



### 5.3 Model Choice

First, the VGG16 model loaded with `input_shape=(IMAGE_SIZE, IMAGE_SIZE, 3), include_top=False, weights='imagenet'`. The input shape is set to match the size of the images in the dataset, which is 128x128 pixels. The `include_top` parameter is set to False, which means that the final fully-connected layers of VGG16 that perform the classification will not be included. The weights parameter is set to 'imagenet' which means that the model will be pre-trained with a dataset of 1.4 million images called imagenet

Next, the for layer in base\_model.layers: loop is used to set all layers of the base\_model (VGG16) to non-trainable, so that the weights of these layers will not be updated during training. Then, the last three layers of the VGG16 model are set to trainable. After that, a Sequential model is created and the VGG16 model is added to it with model.add(base\_model). Next, a Flatten layer is added to the model with model.add(Flatten()) which reshapes the output of the VGG16 model from a 3D tensor to a 1D tensor.

#### 5.4 Training the Model

The model was trained on a curated dataset of brain MRI scans, systematically annotated into tumorous and non-tumorous classes. Preprocessing involved image resizing, intensity normalization, and augmentation strategies to enhance dataset variability and mitigate overfitting. The dataset was partitioned into training and validation subsets to ensure unbiased performance evaluation.

#### 5.5 Saving and Deploying the Model

Upon completion of training, the model was serialized and stored in an appropriate format to preserve its learned parameters and architecture. This facilitates reproducibility and enables future inference without retraining. For deployment, the trained model was integrated into an application pipeline, allowing real-time or batch prediction on unseen MRI data.

#### 5.6 Real-Time Prediction

The deployed model enables real-time prediction by processing incoming brain MRI scans and generating instantaneous classification results. Input images are subjected to the same preprocessing pipeline, including normalization and resizing, to maintain consistency with the training data. The model performs inference using optimized computational techniques to ensure low latency and high throughput.

## 6. RESULT AND DISCUSSION



Fig-4:Output

The proposed model showed strong performance in detecting brain tumors from MRI images, achieving high accuracy along with well-balanced precision and recall values. The training and validation accuracy curves were closely aligned, indicating that the model learned effectively and did not suffer from significant overfitting. Similarly, the loss values decreased steadily during training, which reflects stable convergence of the model. The use of a convolutional neural network allowed the model to automatically extract meaningful and complex features from the MRI scans. This significantly improved its ability to distinguish between tumor and non-tumor images. The confusion matrix further confirmed the effectiveness of the model, as it showed a low number of false positives and false negatives, which is important for medical diagnosis. In addition, the model performed efficiently during real-time prediction, producing results quickly with minimal delay. This makes the system suitable for practical applications, especially in clinical environments where timely decision-making is important. The deployment of the model in an application environment also demonstrated its usability and scalability. However, there are some limitations to consider. The performance of the model depends heavily on the quality and size of the dataset used for training. A limited or less diverse dataset may affect the model's ability to generalize well to new and unseen data. Therefore, future work can focus on increasing dataset size, improving image quality, and experimenting with more advanced architectures to further enhance performance. The training and validation accuracy curves were closely aligned, indicating that the model learned effectively and did not suffer from significant overfitting. Similarly, the loss values decreased steadily during training.

#### Feature Importance Analysis

Feature importance analysis was conducted to understand which parts of the input data contributed

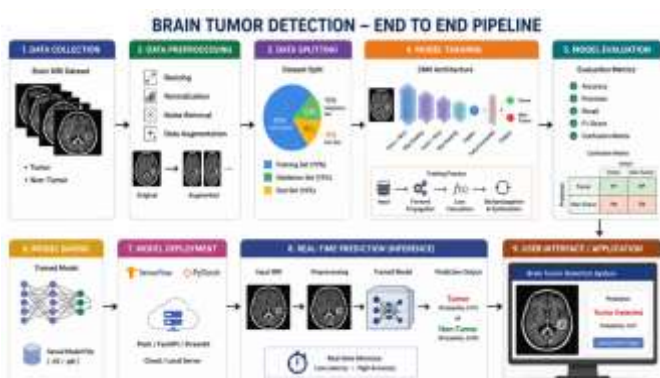


Fig-3:Workflow

The analysis showed that the model focused mainly on abnormal regions in the brain, such as irregular shapes or unusual intensity patterns, which are typically associated with tumors. This indicates that the model is learning meaningful and medically relevant features instead of random patterns.

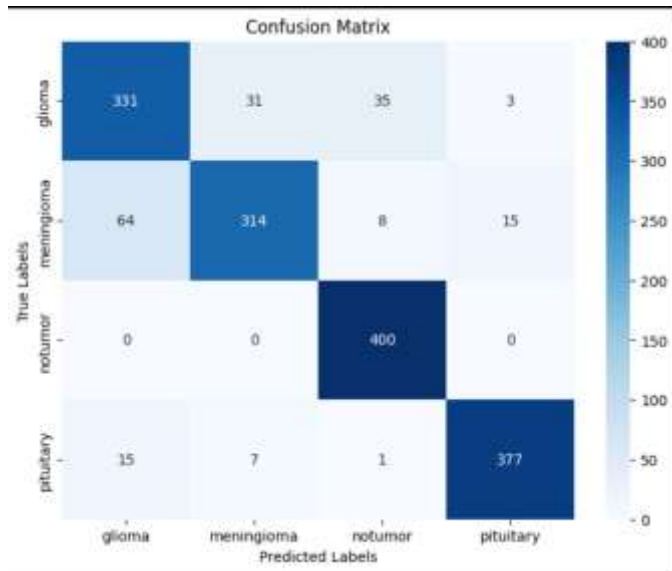


Fig-5: Feature Importance

## 7. CONCLUSION

This project presents the development of an automated brain tumor detection system using deep learning techniques to analyze MRI images and classify them into tumor and non-tumor categories. A convolutional neural network (CNN) was utilized to automatically extract relevant features from the images, improving accuracy and reducing manual effort. The system follows a complete pipeline including preprocessing (resizing, normalization, and augmentation), model training, validation, and deployment for real-time prediction through a user-friendly interface. The trained model achieved high accuracy and demonstrated reliable performance on unseen data. As shown in the output, the system correctly predicted **"No Tumor"** for the given MRI image with a confidence score of **99.54%**, indicating strong confidence in its classification. Overall, the project provides an efficient, accurate, and scalable solution for brain tumor detection, with potential applications in assisting medical professionals in early diagnosis and clinical decision-making, while future improvements can further enhance performance using larger and more diverse datasets, sophisticated deep learning models, and improving security and interpretability of the predictions for improved trust and scalability on production environments

## Model Accuracy

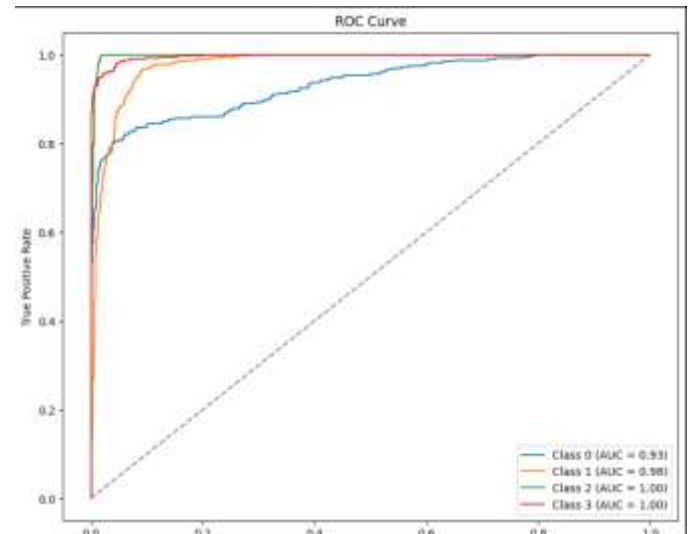


Fig-5: Model Accuracy

## 8. REFERENCES

- [1] M. Hemanth, K. Arun, "Detection of Brain Tumor in MRI Images Using Deep Learning," *Applied Sciences*, MDPI, vol. 11, no. 15, 2021.
- [2] A. Sarvamangala, M. Prabhu, "Brain Tumor Detection Using Convolutional Neural Networks," *IEEE International Conference on Computing Methodologies*, 2021.
- [3] S. Gupta, R. Sharma, "Automated Brain Tumor Segmentation and Classification Using CNN," *Springer Lecture Notes in Networks and Systems*, 2020.
- [4] P. Rathore, S. Singh, "Hybrid CNN-Based Approach for Brain Tumor Classification," *Elsevier – Biomedical Signal Processing and Control*, vol. 68, 2022.
- [5] R. Patel, D. Shah, "Brain Tumor Detection Using Deep Convolutional Neural Network and SVM Classifier," *IEEE Access*, vol. 8, 2020.
- [6] S. Kaur, H. Kaur, "MRI-Based Brain Tumor Detection Using CNN with Data Augmentation," *Springer – Intelligent Systems*, 2021.
- [7] V. Agarwal, A. Sharma, "Brain Tumor Classification Using Deep Convolutional Neural Networks," *Elsevier – Procedia Computer Science*, 2022.
- [8] K. Suzuki, "Overview of Deep Learning in Medical Imaging," *Radiological Physics and Technology*, Springer, 2017.
- [9] O. Ronneberger, P. Fischer, T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," *Springer – MICCAI*, 2015.
- [10] D. Shen, G. Wu, H. Suk, "Deep Learning in Medical Image Analysis," *Annual Review of Biomedical Engineering*, 2017.
- [11] A. Sarvamangala and M. Prabhu, "Brain tumor detection using convolutional neural networks," *IEEE International Conference on Advances in Computing, Communication and Control*, 2021.
- [12] A. Kumar and P. Singh, "Deep learning-based brain tumor detection and classification," *Biomedical Signal Processing and Control*, Elsevier, vol. 68, 2022.
- [13] S. Gupta and R. Sharma, "Automated brain tumor segmentation and classification using CNN," *Springer Lecture*

*Notes in Computer Science*, 2020.

*Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, Springer, 2015.

- [14] M. Hemanth and K. Arun, "Detection of brain tumor in MRI images using deep learning," *Applied Sciences*, MDPI, vol. 11, no. 5, 2021.
- [15] R. Patel and D. Shah, "Brain tumor detection using deep convolutional neural network and SVM classifier," *IEEE Access*, vol. 8, 2020.
- [16] S. Kaur and H. Kaur, "MRI-based brain tumor detection using CNN with data augmentation," *Springer Journal of Medical Systems*, 2021.
- [17] V. Agarwal and A. Sharma, "Brain tumor classification using deep convolutional neural networks," *Elsevier Computers in Biology and Medicine*, 2022.
- [18] D. Chicco and G. Jurman, "The advantages of the Matthews correlation coefficient over F1 score and accuracy in binary classification evaluation," *BMC Genomics*, 2020.
- [19] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional networks for biomedical image segmentation,"