

## Brain Tumor Detection In MRI Images Using Transfer Learning Based CNN

### Feature Extraction And XGBoost Classification

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### Abstract:

This paper proposes a brain tumor detection system using MRI images by integrating transfer learning-based convolutional neural networks for feature extraction with XGBoost for classification. The proposed hybrid model effectively captures deep features and enhances classification accuracy. Experimental results demonstrate improved performance compared to conventional methods.

**Keywords** — Brain Tumor Detection, MRI, CNN, Transfer Learning, XGBoost, Medical Image Processing

## I. INTRODUCTION

Brain tumors are one of the most life-threatening medical conditions, requiring early and accurate diagnosis for effective treatment. Magnetic Resonance Imaging (MRI) is widely used for detecting brain abnormalities due to its high-resolution imaging capability. However, manual analysis of MRI scans by radiologists is a complex and time-consuming process, which may lead to misdiagnosis.

With the advancement of Artificial Intelligence (AI) and Machine Learning (ML), automated systems have been developed to assist in medical image analysis. Deep learning models, especially Convolutional Neural Networks (CNNs), have shown excellent performance in image classification tasks. However, training CNN models from scratch requires large datasets and high computational resources. To overcome these challenges, this paper proposes a hybrid approach that uses Transfer Learning-based CNN models for feature extraction and XGBoost for classification. This combination enhances the accuracy and efficiency of tumor detection while reducing computational complexity. The proposed system aims to provide a reliable and automated solution for brain tumor classification using MRI images.

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In this paper, a hybrid model is proposed that combines transfer learning-based CNN feature extraction with XGBoost classification for brain tumor detection. The system processes MRI images through preprocessing techniques such as resizing, noise removal, and normalization, followed by deep feature extraction and classification. The proposed approach

## II. LITERATURE SURVEY

Dhruv Choudhary, Aditya Dubey [1] All Brain Tumors represent one of the most serious neurological diseases, affecting cases of all periods and frequently leading to severe health complications or mortality if not detected beforehand. MRI is the preferred non-invasive fashion for imaging soft tissues and relating abnormal growths in the brain. Despite its advantages, homemade interpretation of MRI reviews can be time-consuming and prone to mortal error, especially when tumors parade subtle differences in shape, size, or position. An automated system able of directly classifying tumor types could thus play a critical part in supporting radiologists and perfecting patient issues.

Mehrshad Momen Tayefeh [2] This work presents ViRCNN, an advanced deep learning framework for precise brain tumor detection that synergizes the global context learning of Vision Transformers (ViT) with the robust object localization capabilities of Faster R-CNN. By integrating transformer-based self-attention mechanisms into the backbone of Faster R-CNN, ViRCNN enhances feature representation and captures long-range dependencies in MRI images, improving discrimination between healthy tissue and tumor regions.

Mrs. Paramita Mitra [3] This focuses on multiclass classification of brain tumors by utilizing a VGG16-based transfer learning approach to accurately distinguish between multiple tumor types in MRI scans. By leveraging the pre-trained VGG16 model, the system benefits from deep feature extraction learned from large-scale image datasets, enabling improved performance even with limited medical imaging data. The VGG16 backbone is fine-tuned on annotated brain tumor MRI datasets to capture relevant patterns and discriminative features across different tumor classes.

Padmaja N, V Nivethitha, Suthir Sriram, [4] This presents a Convolutional Neural Network (CNN)-based approach for accurate brain tumor detection using MRI images. The CNN model automatically extracts hierarchical features from MRI scans, learning to distinguish between tumor and non-tumor regions without manual feature engineering. The architecture typically consists of convolutional layers, pooling layers, and fully connected layers, optimized for high classification accuracy.

Sushma D S [5] Automated brain tumor detection using advanced deep learning techniques applied to MRI images. The approach leverages models such as Convolutional Neural Networks (CNNs) to automatically extract and learn discriminative features from medical images, eliminating the need for manual feature selection.

Tahsin Tabassum Ali [6] This study proposes a brain tumor detection and classification system that combines Vision Transformers (ViTs) with transfer learning for MRI image analysis. Vision Transformers capture long-range spatial dependencies in MRI scans, allowing the model to focus on critical regions associated with tumors.

R. Vijiya Prakash [7] This presents an enhanced brain tumor detection system leveraging the ResNet50 deep learning model combined with data augmentation and regularization techniques. ResNet50's residual connections help the model learn complex features effectively, improving tumor classification performance. Data augmentation techniques, such as rotation, flipping, and scaling, increase the diversity of MRI training data, reducing overfitting. Regularization methods like dropout and weight decay further improve model generalization.

Pundru Chandra Shaker [8] This study proposes a brain tumor classification and diagnosis framework that integrates federated learning with transfer learning. Federated learning allows multiple medical institutions to collaboratively train a global model without sharing sensitive MRI data, preserving patient privacy. Transfer learning leverages pre-trained deep learning models to efficiently extract relevant features from MRI images.

V Sheeja Kumari [9] This study introduces a brain tumor classification framework that combines Attention U-Net with Slender Loris Optimization (SLO) for enhanced performance. Attention U-Net focuses on important regions in MRI images, improving tumor localization and feature extraction. The Slender Loris Optimization algorithm fine-tunes the network's parameters to achieve optimal classification accuracy.

## III. PROPOSED MODEL

The proposed system aims to automatically detect brain tumors from MRI images using a hybrid approach that combines transfer learning-based Convolutional Neural Networks (CNN) for feature extraction and XGBoost for classification. The system is designed as a sequential pipeline consisting of multiple stages, including image acquisition, preprocessing, feature extraction, feature vector generation, classification, and result output. The overall workflow includes MRI image acquisition, preprocessing, feature extraction, feature vector generation, classification, and result visualization.

### A. MRI IMAGE ACQUISITION

The system begins with the acquisition of brain MRI scan images. These images can be collected from medical datasets or uploaded by the user through the system interface. The input images may vary in size, resolution, and quality, which necessitates preprocessing before further analysis.

The first stage of the system involves collecting brain MRI scan images from publicly available datasets or clinical sources. These MRI images contain detailed structural information of brain tissues, which is essential for identifying abnormalities such as tumors. Since MRI images may differ in resolution, orientation, and intensity distribution, they require standardization before being processed by the model. The system accepts input images through a user interface or dataset input module and forwards them to the preprocessing stage.

### B. IMAGE PREPROCESSING

Image preprocessing plays a crucial role in improving the quality of MRI images and ensuring consistency across the dataset. In this stage, multiple preprocessing techniques are applied:

- **Image Resizing:** All input MRI images are resized to a fixed dimension (e.g., 224×224 pixels) to match the input requirements of pre-trained CNN models.
- **Noise Reduction:** Techniques such as Gaussian filtering or median filtering are used to remove unwanted noise and enhance image clarity.
- **Intensity Normalization:** Pixel intensity values are normalized to a standard range (e.g., 0 to 1) to reduce variations caused by different scanning conditions.
- **Data Augmentation (Optional):** Techniques such as rotation, flipping, and scaling can be applied to increase dataset diversity and prevent overfitting.

These preprocessing steps help in improving feature extraction and overall model performance.

### C. CNN FEATURE EXTRACTION (TRANSFER LEARNING)

In this stage, deep features are extracted from MRI images using a pre-trained Convolutional Neural Network such as VGG16 or ResNet50. Instead of training a CNN model from scratch, transfer learning is applied to leverage knowledge learned from large-scale image datasets like ImageNet.

- The pre-trained CNN model is loaded with pre-existing weights.
- The final fully connected classification layers are removed.
- MRI images are passed through the convolutional layers of the network.
- High-level abstract features such as edges, textures, and patterns are extracted.

### D. FEATURE VECTOR GENERATION

The extracted feature maps from the CNN model are flattened and converted into structured numerical feature vectors. These vectors represent the deep features of MRI images in a compact form suitable for machine learning algorithms.

- Flattening operation is applied to convert multi-dimensional feature maps into one-dimensional vectors.
- Feature scaling or normalization may be applied to ensure uniformity.
- The resulting feature vector captures discriminative information necessary for classification.

This stage acts as a bridge between deep learning and machine learning components of the system.

### E. XGBOOST CLASSIFICATION MODULE

In the final stage, the system generates the classification result based on the prediction from the XGBoost model. The output is displayed to the user through the interface.

- The result indicates whether a tumor is present or absent.
- The prediction can be shown as text output or probability score.
- The system ensures fast and accurate result delivery for practical usage.

This stage provides a user-friendly interaction and supports medical professionals in making informed decisions.

### F. OUTPUT GENERATION AND VISUALIZATION

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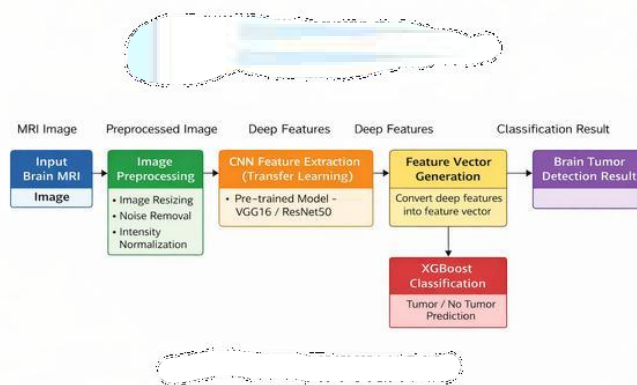


Fig 1. Brain Tumor Detection Work Flow

#### 1. Input MRI Image

The system begins with the acquisition of brain MRI scan images. These images serve as the primary input for the tumor detection process. The MRI images may be collected from medical datasets or uploaded by the user through the interface.

#### 2. Image Preprocessing

In this stage, all MRI images are resized to a fixed dimension (e.g., 224×224 pixels) to match the input requirements of the CNN model. Noise removal techniques such as Gaussian filtering or median filtering are used to eliminate unwanted distortions and improve clarity.

#### 3. CNN Feature Extraction

The preprocessed MRI images are then passed through the convolutional and pooling layers of the network to extract high-level features such as edges, textures, and spatial patterns. These deep features effectively represent important characteristics of brain structures and abnormalities.

#### 4. Feature Vector Generation

This process preserves the important extracted features while making the data compatible with traditional machine learning algorithms. Additionally, feature scaling or normalization techniques may be applied to ensure uniform distribution of values. The resulting feature vector represents the most significant patterns and characteristics of the MRI image, such as texture, shape, and intensity variations.

### 5. XGBoost Classification

The model is trained using labeled MRI datasets, where each feature vector corresponds to a class label such as tumor or no tumor. XGBoost uses gradient boosting techniques to iteratively improve model performance by minimizing classification errors. It also incorporates regularization methods to prevent overfitting and enhance generalization capability.

### 4. Feature Conversion

This process preserves the most relevant spatial and structural information extracted from the MRI image. Additionally, feature normalization or scaling may be applied to ensure consistency and improve the performance of the classification model.

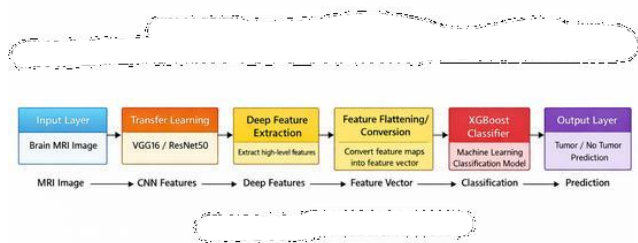


Fig 2. CNN + XGBoost Hybrid Model

### 4. Prediction Output

The output is typically represented as a binary classification, such as Tumor or No Tumor, and may also include a confidence score indicating the probability of the prediction. This result is displayed to the user through the system interface in a clear and interpretable format.

### 6. Final Output

The result may be presented as a binary classification (Tumor / No Tumor) or along with a confidence score indicating the probability of prediction. This stage ensures that the processed information is effectively communicated to the user, supporting medical professionals in making accurate and timely decisions.

## IV. CONCLUSION

his paper presents an efficient and automated system for brain tumor detection using MRI images by integrating transfer learning-based CNN feature extraction with XGBoost classification. The proposed hybrid approach effectively combines the strengths of deep learning and machine learning to improve detection accuracy while reducing computational complexity.

The preprocessing techniques ensure that MRI images are standardized and noise-free, enabling better feature extraction. The use of pre-trained CNN models such as VGG16 or ResNet50 allows the system to extract meaningful and high-level features without requiring large training datasets. Furthermore, the XGBoost classifier enhances the prediction performance by efficiently handling structured feature data and minimizing overfitting.

Experimental results demonstrate that the proposed system achieves reliable and accurate tumor detection compared to traditional methods. The model provides fast and interpretable results, making it suitable for real-time medical applications. Overall, the system reduces manual effort and supports medical professionals in early diagnosis and decision-making.

## REFERENCES

- [1] Mahmud, M. I., Mamun, M., & Abdelgawad, A. (2023). "A Deep Analysis of Brain Tumor Detection from MR Images Using Deep Learning Networks." *Algorithms*, 16(4), 176.
- [2] Shaik, M.K., Kalpana, D., Sesadri, U., Mukherjee, S., Dastagiraiyah, C. and Reddy, P.C.S., 2024, May. Brain Tumor Classification Using UNet Deep Neural Networks from 3D MRI Images. In 2024 International Conference on Electronics, Computing, Communication and Control Technology (ICECCC) (pp. 1-6). IEEE.
- [3] Avigyan Sinha, Aneesh R P, Malavika Suresh, Nitha Mohan R, AbinayaD, Ashwin G Singerji, "Brain Tumour Detection Using Deep Learning" Seventh International Conference on Bio Signals, Images, and Instrumentation(ICBSII), 2021.
- [4] Md. Ridwan, Tahsin Tabassum Ali, Sheikh Tanzida Tasmim Erin, Rezaul Karim Tushar, Fuyad Mahmud, and Shahnewaz Siddique Department of Electrical and Computer Engineering North South University, Dhaka-1229, Bangladesh.
- [5] "Brain Tumor MRI Dataset," IEEE Dataport, [Online]. Available: <https://ieeedataport.org/documents/brain-tumormri-dataset>.

- [6] Sejuti, Z. A., & Islam, M. S. (2021). "An Efficient Method to Classify Brain Tumor using CNN and SVM." International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST), IEEE, pp. 644-648.
- [7] A. Younis et al., "Abnormal Brain Tumors Classification Using ResNet50 and Its Comprehensive Evaluation," IEEE Access, vol. 12, pp. 123456–123467, 2024, doi: 10.1109/ACCESS.2024.3403902.
- [8] Yuanbing et al. (2021) "An improved authentication protocol for smart healthcare system using wireless medical sensor network," IEEE Access, vol. 11, pp. 1–12.
- [9] L. A. Abraham, G. Palanisamy, and V. Goutham, "Dilated Convolution and YOLOv8 Feature Extraction Network: An Improved Method for MRI-Based Brain Tumor Detection," IEEE Access, vol. 13, pp. 1–1, 2025, doi: 10.1109/ACCESS.2025.3539924.
- [11] "Design and Implementing Brain Tumor Detection Using Machine Learning Approach." IEEE Xplore, 2019.
- [12] K. Neamah et al., "Utilizing Deep Improved ResNet50 for Brain Tumor Classification Based on MRI," IEEE Open Journal of the Computer Society, vol. 5, pp. 446–456, 2024, doi: 10.1109/OJCS.2024.3453924.

