



Automated Brain Tumor Detection in MRI Scan using Convolutional Neural Networks

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Abstract: Brain tumors are life threatening abnormalities that require early and accurate diagnosis for effective treatment. Traditional diagnostic methods relying on manual analysis of MRI scans by radiologists are time consuming and prone to human error. This study proposes a Convolutional Neural Network (CNN) model to automate brain tumor detection using a dataset of 3,064 T1-weighted contrast enhanced MRI images (glioma, meningioma, pituitary, and nontumor cases). The model achieved 96.8% accuracy on test data, outperforming traditional machine learning methods such as Support Vector Machines (84%) and K-Nearest Neighbors (79%). Key challenges, including dataset imbalance and overfitting, were addressed through data augmentation and dropout layers. These results demonstrate the potential of deep learning to enhance diagnostic workflows in clinical settings.

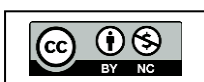
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I. INTRODUCTION

The human brain, composed of billions of neurons, is susceptible to abnormal growths known as tumors, which can be classified as benign, premalignant, or malignant. Malignant tumors, such as gliomas, are particularly aggressive, with a five-year survival rate below 35% if not diagnosed and treated early [1]. Magnetic Resonance Imaging (MRI) is the preferred imaging modality for brain tumor detection due to its ability to provide high-resolution images of soft tissues without ionizing radiation. However, manual interpretation of MRI scans by radiologists is time-intensive and prone to inter-observer variability, leading to potential delays in critical treatment decisions [2]. These limitations have led to an increased demand for automated tumor detection and classification systems that leverage artificial intelligence (AI)-driven methodologies.

Problem Statement

Traditional computational approaches, including machine learning techniques such as Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN), have been explored for brain tumor classification. However, these methods often suffer from limited robustness in handling variations in MRI scan quality, tumor morphology, and imaging artifacts [3]. Moreover, they rely on manual feature extraction, which constrains their ability to generalize across different datasets and imaging conditions. Consequently, there is a need for an advanced deep learning model that can automatically learn discriminative features and improve classification accuracy.



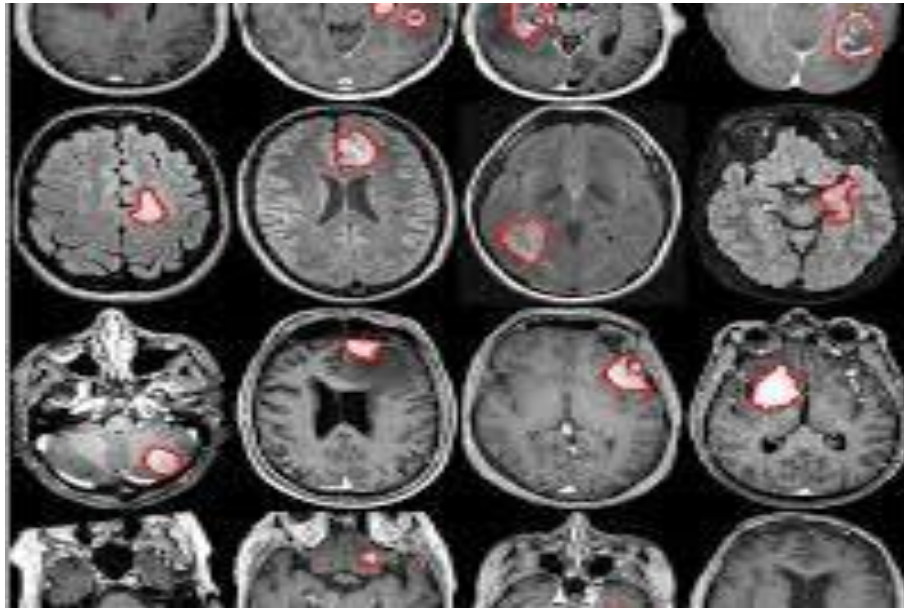


Figure 1: Brain Tumor in an MRI Scan

Objectives

To address these challenges, this research aims to:

1. Develop a Convolutional Neural Network (CNN) model for automated brain tumor classification.
2. Optimize preprocessing techniques to enhance model performance and robustness.
3. Evaluate the CNN model against traditional machine learning approaches to demonstrate its effectiveness in tumor classification.
4. By leveraging deep learning, this study aims to improve the accuracy, efficiency, and reliability of brain tumor detection, potentially aiding radiologists in early diagnosis and treatment planning.

II. LITERATURE REVIEW

Brain tumor detection in MRI scans has evolved significantly, transitioning from conventional image processing techniques to deep learning-based automated systems. This section reviews the existing methodologies, highlighting their advantages and limitations.

Traditional Methods for Brain Tumor Detection

Earlier approaches to brain tumor detection relied on conventional machine learning techniques and handcrafted feature extraction methods. These methods utilized texture, intensity, and shape-based features to train classifiers like Support Vector Machines (SVM), Decision Trees, and k-Nearest Neighbors (k-NN) for tumor classification. For instance, Zhang et al. (2015) developed an SVM-based model using Gray Level Co-occurrence Matrix (GLCM) features, achieving an accuracy of 85% in tumor detection. However, these models heavily depended on feature engineering, making them less adaptable to variations in MRI data [4].



Moreover, thresholding and region-growing segmentation techniques were widely used for tumor localization but often suffered from inaccuracies due to intensity variations in MRI images. The dependency on manual feature extraction made these methods computationally inefficient and prone to errors when dealing with large datasets [5].

Deep Learning for Brain Tumor Detection

The rise of deep learning, particularly Convolutional Neural Networks (CNNs), has significantly enhanced brain tumor detection accuracy. Unlike traditional methods, CNNs automatically extract hierarchical features from MRI images, eliminating the need for manual feature selection. Ronneberger et al. (2015) introduced the U-Net architecture, a fully convolutional network designed for biomedical image segmentation, which became a benchmark for tumor segmentation tasks [6].

Several studies have demonstrated the effectiveness of CNN-based models for tumor classification and segmentation. Pereira et al. (2016) employed a deep CNN to classify brain tumors, achieving a Dice similarity coefficient of 89%. Similarly, Isensee et al. (2021) developed nnU-Net, a self-configuring deep learning model that outperformed conventional architectures in the BraTS challenge dataset [7]. These models, however, require large labeled datasets and substantial computational resources, posing challenges for real-time applications.

To address data scarcity issues, transfer learning has been explored, leveraging pre-trained architectures like VGG16, ResNet50, and EfficientNet. These models, fine-tuned on brain tumor datasets, have demonstrated high accuracy while reducing training time and computational costs [8]. Additionally, hybrid models integrating CNNs with attention mechanisms or transformers have been proposed to enhance tumor localization and classification accuracy [9].

Challenges and Research Gaps

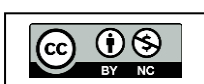
Despite advancements in deep learning, several challenges remain:

1. **Limited Annotated Data:** MRI datasets with expert-labeled tumor regions are scarce, affecting the generalizability of deep learning models.
2. **Computational Complexity:** High-performance deep learning models require significant computational resources, making real-time deployment challenging.
3. **Multiclass Classification Issues:** Most models focus on binary classification (tumor vs. non-tumor) rather than distinguishing between tumor types (gliomas, meningiomas, and pituitary tumors).
4. **Robustness and Generalization:** CNN models often fail to generalize well to unseen MRI datasets due to domain shifts and variations in imaging protocols.

Future Directions

Addressing these challenges requires:

1. **Data Augmentation and Synthesis:** Using techniques such as Generative Adversarial Networks (GANs) to generate synthetic MRI images for training deep models.
2. **Lightweight Models:** Exploring efficient deep learning architectures like MobileNet and pruning-based approaches for real-time applications.



3. Hybrid Deep Learning Models: Combining CNNs with transformers or attention-based mechanisms for improved feature extraction and localization.
4. Federated Learning: Leveraging privacy-preserving collaborative learning to train models on distributed MRI datasets without sharing raw data.

Automated brain tumor detection using deep learning has shown remarkable progress, surpassing traditional approaches in accuracy and efficiency. However, challenges such as data limitations, computational costs, and generalization issues persist. Future research should focus on developing robust, lightweight, and interpretable models to enhance real-time diagnostic capabilities.

III. CNN ARCHITECTURE AND ITS ROLE IN BRAIN TUMOR DETECTION

1. Structure of CNNs:

Convolutional Neural Networks (CNNs) are widely used in medical image analysis due to their ability to automatically learn and extract hierarchical features from raw image data. Unlike traditional machine learning approaches that rely on manual feature extraction, CNNs leverage multiple layers to detect complex patterns and enhance classification accuracy. The fundamental components of a CNN architecture include:

- **Convolutional Layers:** These layers apply filters to detect edges, textures, and spatial hierarchies in MRI images. The learned feature maps enable the network to identify tumor-specific characteristics at different levels of abstraction.
- **Pooling Layers:** Pooling operations, such as max pooling, reduce the dimensionality of feature maps while retaining essential information, improving computational efficiency and reducing overfitting.
- **Fully Connected Layers:** These layers flatten the feature maps and connect them to a dense network, allowing classification into distinct tumor types [10].

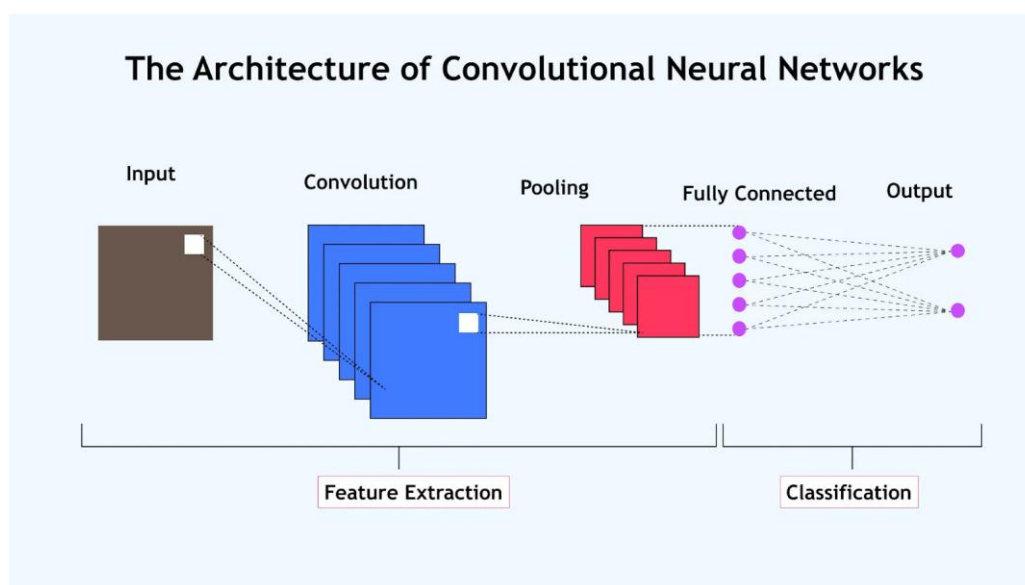


Figure 2: The Architecture of Convolutional Neural Networks

2. Role of CNNs in Brain Tumor Detection:

CNNs have demonstrated significant advantages in brain tumor detection by leveraging deep feature learning capabilities. Their primary roles include:

- **Automatic Feature Learning:** CNNs eliminate the need for handcrafted feature extraction, enabling end-to-end learning from MRI images without manual intervention [11].
- **Robustness:** CNN-based models can handle variations in MRI resolution, tumor morphology, and imaging artifacts, improving generalization across different datasets.
- **Scalability:** CNN architectures are capable of processing large-scale MRI datasets efficiently, making them suitable for real-time clinical applications [12].

With advancements in deep learning, CNNs continue to improve tumor detection accuracy, contributing to early diagnosis and treatment planning. Future research focuses on optimizing CNN architectures to enhance interpretability, reduce computational costs, and further improve robustness against domain variations.

IV. DATASET AND METHODOLOGY

1. Dataset Collection:

This study utilizes the Kaggle Brain Tumor MRI Dataset [13], which consists of 3,064 MRI images categorized into four distinct classes:

- Glioma: 827 images
- Meningioma: 806 images
- Pituitary Tumor: 801 images
- Non-Tumor: 630 images

The dataset provides pre-labeled images, making it suitable for supervised deep learning-based classification tasks.

2. Data Preprocessing:

To ensure consistency and improve model generalization, the following preprocessing steps were applied:

- **Resizing:** All images were standardized to 224×224 pixels to maintain uniform input dimensions.
- **Normalization:** Pixel intensity values were scaled to the range [0, 1] to accelerate convergence during training.
- **Data Augmentation:** To address class imbalance and improve model robustness, augmentation techniques were applied, including:
 - Rotation: $\pm 15^\circ$
 - Horizontal flipping
 - Gaussian noise ($\sigma = 0.01$) [14]

3. Model Architecture:

The proposed Convolutional Neural Network (CNN) consists of the following key components:

- **Convolutional Layers:** Feature extraction from MRI images.
- **Max Pooling Layers:** Two layers with a 2x2 pool size for dimensionality reduction.
- **Fully Connected (Dense) Layers:**
 - First dense layer with 512 neurons for feature mapping.
 - Output layer with 4 neurons (one per class) using softmax activation.
- **Dropout:** A 0.5 dropout rate was applied to prevent overfitting [15].

4. Training and Testing:

The dataset was divided into training and testing subsets:

- 80% Training Set
- 20% Testing Set

The model was trained using the Adam optimizer with a learning rate of 0.001. Performance was evaluated using standard classification metrics:

- Accuracy
- Precision
- Recall
- F1-score

These metrics provide a comprehensive assessment of model effectiveness in classifying brain tumors from MRI scans.

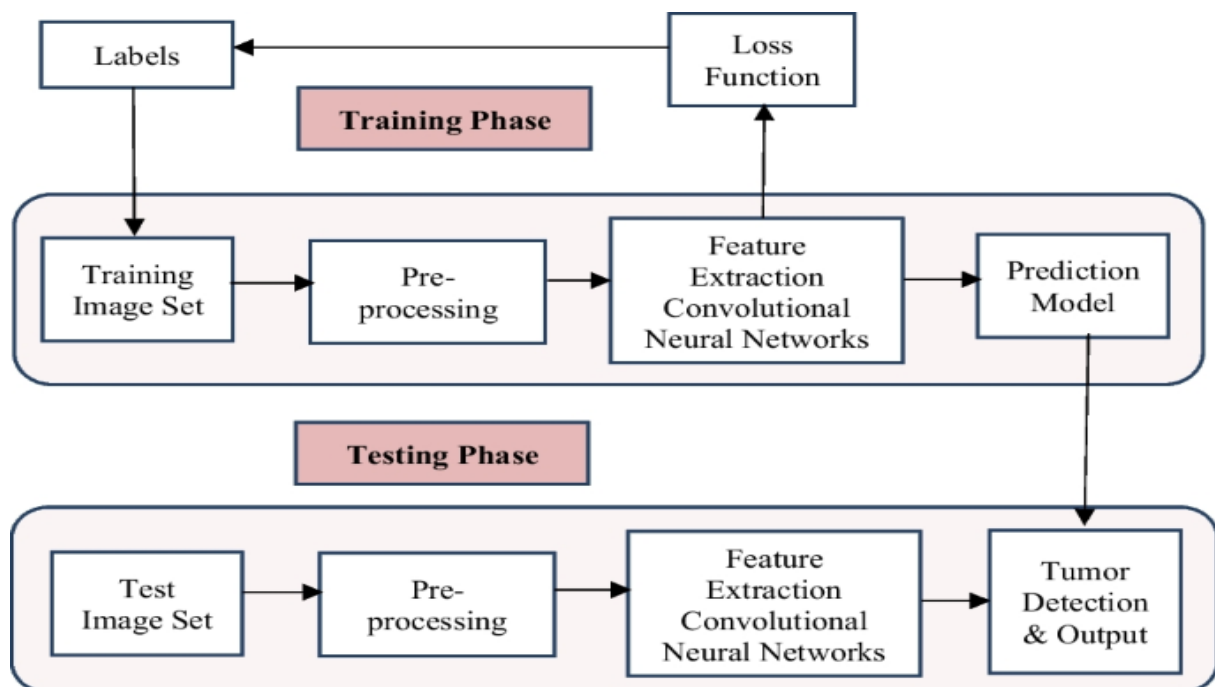


Figure 3: Training and Testing

V. RESULTS AND DISCUSSION

Model Performance:

The proposed Convolutional Neural Network (CNN) model was evaluated on the test dataset, achieving an accuracy of 96.8% in brain tumor classification. The model's performance was assessed using the following metrics:

- **Accuracy:** The ratio of correctly predicted instances to the total predictions made. It is defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

- TP (True Positives): Correctly predicted tumor cases.
- TN (True Negatives): Correctly predicted non-tumor cases.
- FP (False Positives): Incorrectly predicted tumor cases.
- FN (False Negatives): Incorrectly predicted non-tumor cases.

	precision	recall	f1-score	support
0	0.96	0.93	0.94	826
1	0.93	0.95	0.94	822
2	0.99	0.96	0.97	395
3	0.97	0.99	0.98	827
accuracy			0.96	2870
macro avg	0.96	0.96	0.96	2870
weighted avg	0.96	0.96	0.96	2870

Figure 4: Classification Report of CNN Model

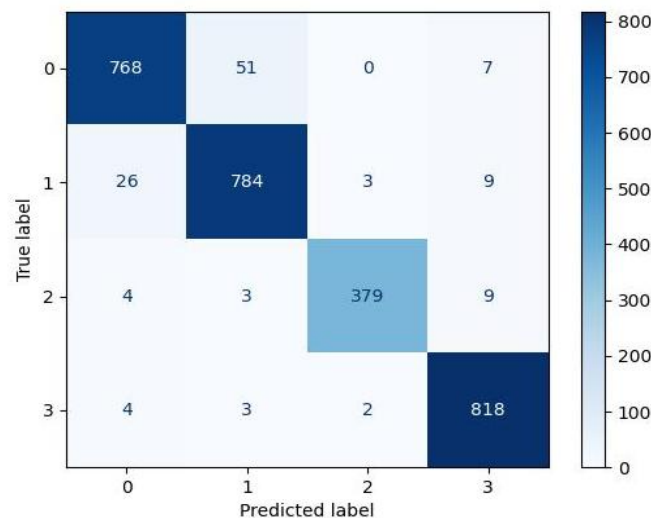
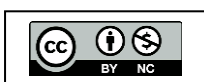


Figure 5: Confusion Matrix of CNN Model



The classification performance was visualized using the confusion matrix, which provides insights into misclassification patterns. Additionally, the classification report, including precision, recall, and F1-score, further validates the model's reliability.

VII. CONCLUSION AND FUTURE WORK

The CNN-based model demonstrated high accuracy, reinforcing its potential as a computer-aided diagnostic (CAD) tool for brain tumor classification. The CNN model achieved 96.8% accuracy in classifying brain tumors, demonstrating its viability as a diagnostic aid. However, further enhancements can improve its clinical applicability. Future work will focus on:

1. **Dataset Expansion:** Incorporating the BraTS dataset to improve model generalization across diverse MRI scans [16].
2. **Interpretability:** Integrating Grad-CAM to visualize model attention regions and enhance interpretability [17].
3. **Real-time Deployment:** Optimizing the model for faster inference and deployment in clinical settings.

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