# NeuralEyes: Brain Tumor Detection from MRI Images Using CNN

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***Abstract - Among neurological disorders, brain tumors present a major diagnostic challenge and require accurate, timely detection to improve patient survival rates. Advances in artificial intelligence have significantly influenced medical image analysis, with deep learning models showing strong capability in classification tasks. This study develops a convolutional neural network (CNN) to categorize brain MRI scans into tumorous and non-tumorous classes.***

***Before model training, a comprehensive preprocessing pipeline was applied that included image resizing, normalization, brain-region extraction, and data augmentation. These techniques were implemented to strengthen feature representation, minimize irrelevant background information, and enhance the model's capacity to generalize across diverse samples. The trained model achieved an approximate test accuracy of 86%, indicating reliable performance in binary classification despite the limited size of the dataset. Furthermore, the model demonstrated stability when evaluated on MRI scans with varying orientations, successfully identifying tumors across different viewing perspectives. This behavior suggests that the network learned discriminative spatial features rather than memorizing training data.***

***Overall, the results demonstrate the value of convolutional neural networks in assisting automated brain tumor detection and underline the importance of well-designed preprocessing strategies in building dependable medical imaging systems. Although the outcomes are encouraging, future work involving larger datasets is recommended to further validate the model and support its applicability in real clinical environments.***

## I. Introduction

Brain tumors are considered one of the most serious medical conditions affecting the human brain, and detecting them at an early stage is essential for improving treatment outcomes. Medical imaging technologies, particularly magnetic resonance imaging (MRI), play a vital role in helping healthcare professionals examine brain structures and identify potential abnormalities. MRI scans provide detailed visual information; however, analyzing these images manually can be challenging, time-consuming, and highly dependent on clinical expertise. For this reason, there is an increasing interest in developing automated systems that can support medical professionals in making faster and more consistent diagnostic decisions.

Artificial intelligence has gradually become an important tool in the field of medical imaging. Among its various branches, deep learning has shown remarkable capability in handling image classification tasks by learning patterns directly from data. Convolutional neural networks (CNNs), in particular, have gained attention due to their effectiveness in extracting spatial features and recognizing visual patterns. These strengths make CNNs a suitable choice for detecting abnormalities such as brain tumors in MRI scans.

In this paper, a convolutional neural network is developed to classify brain MRI images into tumorous and non-tumorous categories. To enhance the learning process, several preprocessing techniques were applied, including image resizing, normalization, brain-region cropping, and data augmentation. These steps were intended to improve feature clarity, reduce unnecessary background information, and help the model adapt to variations within the dataset.

The developed model achieved an accuracy of approximately 86% on the test data and maintained reliable performance when evaluated on MRI scans captured from different orientations. This suggests that the network was able to learn meaningful spatial features rather than simply memorizing training examples. The results demonstrate the growing potential of deep learning in medical diagnostics and highlight how well-designed models can contribute to more efficient and dependable brain tumor detection.

## II. Related Work

Deep learning has become a central part of modern medical image analysis, especially for tasks that involve identifying and classifying diseases. Convolutional neural networks (CNNs) are particularly well suited for this work because they can automatically learn meaningful visual patterns directly from images. Their success has encouraged many researchers to apply CNN based techniques to a wide range of medical imaging challenges.

In the case of brain tumor detection using MRI scans, earlier studies have experimented with different CNN architectures, preprocessing strategies, and data augmentation methods to boost classification accuracy. Preparing MRI images before training such as reducing noise or enhancing important structures has consistently been shown to improve model performance by making key features easier for the network to recognize.

Some researchers have pushed performance further by using transfer learning or hybrid deep learning models, allowing networks to build on previously learned visual representations. Others have focused on segmentation driven approaches to pinpoint tumor regions more precisely. While many of these methods report strong results, their success often depends on factors like dataset quality, model design, and the diversity of the training samples.

Building on these developments, this study uses a CNN based classification model supported by structured preprocessing steps, including cropping the brain region and applying data augmentation. The goal is to create a system that performs reliably while remaining adaptable to the natural variations found in MRI images.

## III. Methodology

This study presents a convolutional neural network (CNN) designed to classify brain MRI scans as either containing a tumor or showing no signs of one. The process involves several key steps: assembling the dataset, preparing and enhancing the images, applying data-augmentation techniques, building the CNN model, and assessing its performance. Each component of the workflow is structured to support strong feature learning and improve the consistency and accuracy of the final classification results.

### A. Dataset

The dataset for this research includes 253 MRI brain scans, separated into two groups: images showing tumors and images of healthy brains. Out of the total, 155 scans contain visible tumors, while 98 belong to the non-tumorous class. This uneven split introduces a mild class imbalance, which was taken into consideration during model training.

Even with its limited size, the dataset offers enough visual detail for a supervised deep learning model to learn the distinctions between normal brain anatomy and tumor-affected regions

### B. Image Preprocessing

Medical images often contain background details that do not contribute to the learning process and may introduce unnecessary noise. To improve data quality and support effective feature extraction, several preprocessing steps were applied before training the model.

First, all MRI images were resized to a consistent dimension to ensure uniform input into the neural network. Standardizing image size helps stabilize training and prevents computational inconsistencies. Pixel values were then normalized to scale the data within a similar range, allowing the model to learn more efficiently.

In addition, brain-region cropping was performed to remove irrelevant background areas and focus the model's attention on the anatomical structures of interest. By isolating the brain from surrounding artifacts, this step enhances feature clarity and supports the network in learning patterns that are more meaningful for tumor detection. This approach also helps reduce noise within the dataset, contributing to improved model performance.

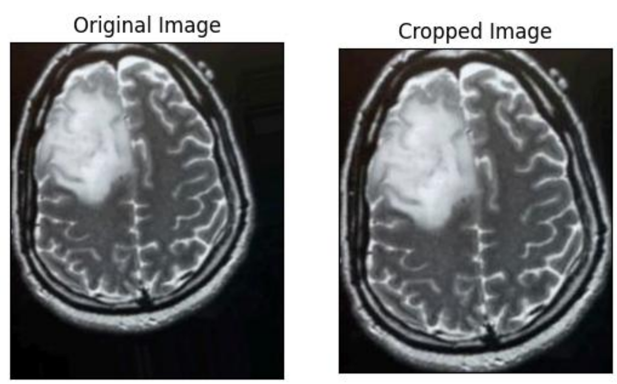


FIGURE 1. Example of MRI image before and after brain-region cropping.

### C. Data Augmentation

Deep learning models generally perform better when trained on large datasets, as greater data diversity helps the network learn more reliable patterns. In this study, the available dataset was relatively limited, which introduced a higher risk of overfitting a scenario where the model performs well on training data but struggles with unseen images. To reduce this risk and strengthen the learning process, data augmentation techniques were applied to the training set.

Transformations such as rotation, flipping, and scaling were used to generate additional variations of the existing images. These modifications expose the model to different visual perspectives, encouraging it to focus on meaningful tumor characteristics rather than memorizing specific image positions. As a result, the network becomes more adaptable and better equipped to handle variations commonly found in real MRI scans.

Augmentation was intentionally restricted to the training data to prevent data leakage and maintain a fair evaluation process. This ensures that validation and test results provide an accurate representation of the model's ability to generalize to new, unseen data.

### D. *Model Architecture*

The classification model was constructed using a convolutional neural network designed to learn visual representations directly from brain MRI scans. The network processes each image through sequential convolution operations that enable the detection of structural patterns associated with tumor presence.

Feature extraction is performed by applying multiple filters that respond to variations in intensity, shape, and texture within the images. Non-linear activation is introduced using the Rectified Linear Unit (ReLU), allowing the network to capture complex feature interactions. Spatial resolution is then reduced through max-pooling, which preserves dominant features while lowering computational requirements.

The extracted representations are subsequently transformed into a one-dimensional vector and forwarded to dense layers that perform the final decision-making process. The output stage utilizes a sigmoid activation function to estimate the probability of tumor occurrence, supporting binary classification.

Model capacity was intentionally moderated to align with the dataset size, reducing the likelihood of overfitting while maintaining sufficient learning capability.

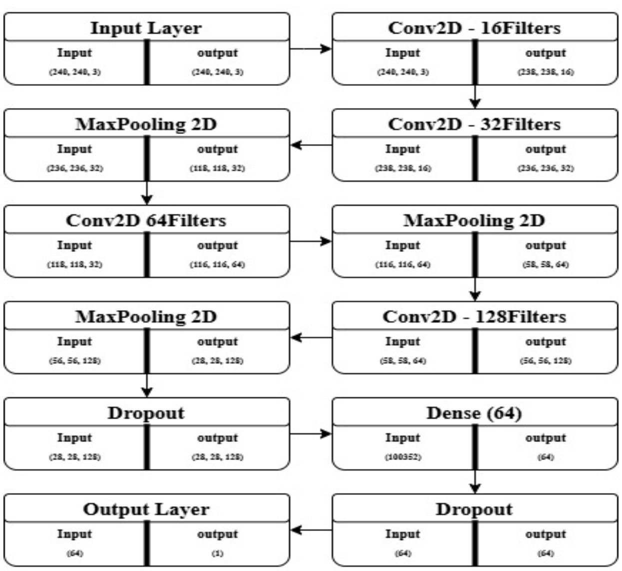


FIGURE 2. ARCHITECTURE OF THE PROPOSED CONVOLUTIONAL NEURAL NETWORK FOR BRAIN TUMOR CLASSIFICATION.

### E. *Training Strategy*

The model was trained using a supervised learning approach, where labeled MRI images guided the network in distinguishing between tumorous and non-tumorous cases. The dataset was divided into training, validation, and testing subsets to ensure reliable performance evaluation.

Binary cross-entropy was used as the loss function, as the task involves binary classification. Model parameters were optimized using the Adam optimizer, which enabled efficient convergence during training.

To further improve training stability and reduce overfitting, early stopping was implemented to monitor validation performance and halt training when no significant improvement was observed. Additionally, model checkpointing was used to preserve the best-performing model for final evaluation.

## IV. RESULTS

To evaluate the effectiveness of the proposed model, predictions were generated using MRI images that were not included in the training phase. This approach provides a clearer indication of how the network performs when exposed to new data. Accuracy and loss were used as the primary indicators of performance.

The model reached an accuracy of approximately 86% on the test set, reflecting its capability to correctly classify the majority of brain scans. Considering the moderate size of the dataset, this outcome suggests that the network was able to capture important visual characteristics associated with tumor presence.

The training process was further analyzed through accuracy and loss curves. As shown in Figure.3, both training and validation accuracy demonstrate a steady upward trend, indicating that the model progressively improved during learning. Similarly, the loss curve presented in Figure.4 shows a continuous decline, suggesting that prediction errors decreased over time.

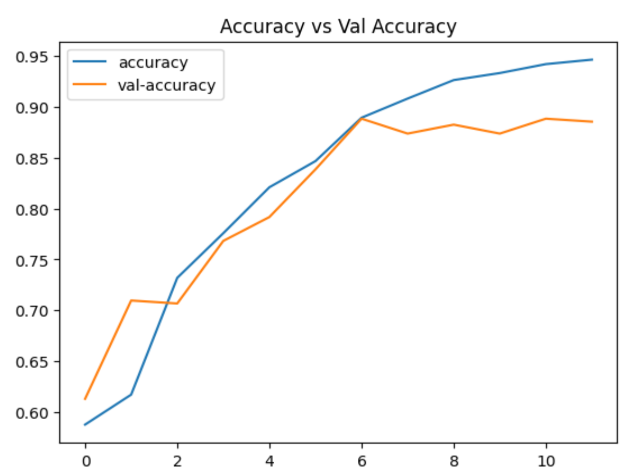


FIGURE 3. TRAINING AND VALIDATION ACCURACY ACROSS EPOCHS.

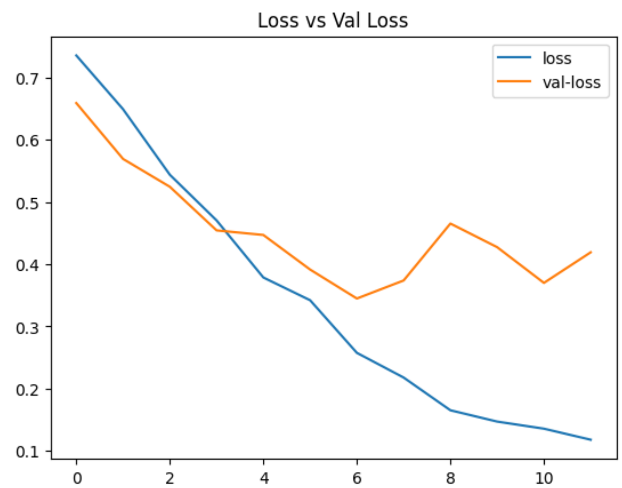


FIGURE 4. TRAINING AND VALIDATION LOSS ACROSS EPOCHS.

### A. *Evaluation on Standard MRI Scans*

The model was first evaluated on MRI scans captured under a similar viewing orientation to those used during training. This step was intended to establish the model's baseline classification behavior before examining more challenging orientation changes.

The network correctly identified both tumorous and non-tumorous cases, suggesting that it learned relevant visual features necessary for reliable prediction. Example outputs are shown in Figure. 5.

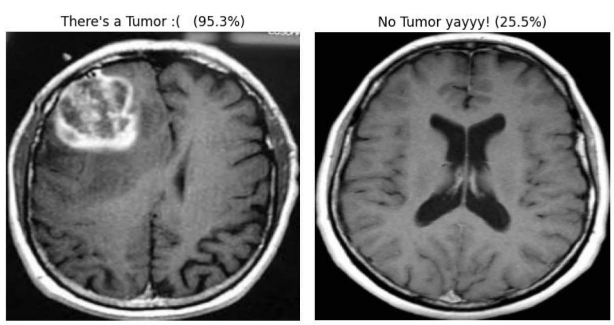


FIGURE 5. MODEL PREDICTIONS UNDER STANDARD IMAGING ORIENTATION: TUMOROUS MRI SCAN (LEFT) AND NON-TUMOROUS MRI SCAN (RIGHT).

### B. *Evaluation on MRI Scans with Varying Orientations*

To further investigate the robustness of the proposed model, additional MRI scans captured from different orientations were evaluated. Variations in scan alignment can introduce spatial differences that challenge classification models. Despite these changes, the network maintained accurate predictions for both tumorous and non-tumorous cases, as illustrated in Figure. 6.

This outcome suggests that the model learned spatially meaningful features rather than relying on fixed positional patterns. Such behavior indicates a degree of orientation invariance, which is desirable in medical image classification where scan alignment may vary.

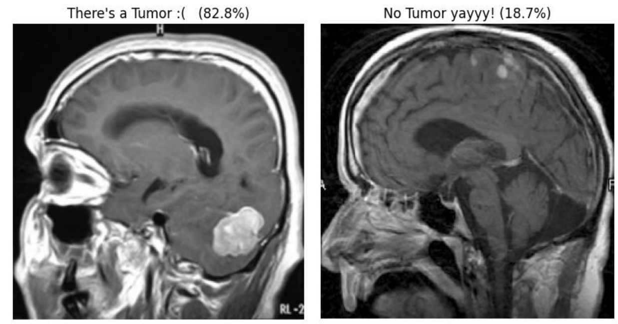


FIGURE 6. MODEL PREDICTIONS ON MRI SCANS CAPTURED FROM DIFFERENT ORIENTATIONS: TUMOROUS BRAIN SCAN (RIGHT) AND NON-TUMOROUS BRAIN SCAN (LEFT), BOTH CORRECTLY CLASSIFIED DESPITE VARIATION IN VIEWING ANGLE.

## V. DISCUSSION

The results indicate that the proposed convolutional neural network was able to learn meaningful patterns from brain MRI images and perform reliable binary classification. Achieving an accuracy of 86% suggests that the model developed a strong ability to differentiate between tumorous and non-tumorous scans despite the moderate dataset size.

The steady improvement observed in both accuracy and loss curves reflects stable learning behavior throughout training. Although a slight separation between training and validation metrics emerged in later epochs, the gap remained controlled, implying that overfitting was limited and did not significantly affect overall performance.

Several factors likely contributed to the model's effectiveness, including structured preprocessing, brain-region cropping, and the application of data augmentation. These steps helped improve feature clarity and allowed the network to generalize better when exposed to unseen data.

Despite these encouraging outcomes, certain limitations should be acknowledged. The dataset size remains relatively constrained, and expanding it could further enhance model robustness. Future work may explore deeper architectures, transfer learning techniques, or larger medical datasets to strengthen predictive capability.

## VI. CONCLUSION

This study introduced a convolutional neural network designed to detect brain tumors from MRI images with a reliable level of accuracy. By integrating structured preprocessing, targeted data augmentation, and a progressively deep architecture, the model was able to extract meaningful visual features and translate them into dependable classification decisions.

Achieving an accuracy of approximately 86%, the model demonstrated strong predictive capability despite being trained on a moderately sized dataset. More importantly, its consistent performance on scans captured from varying orientations suggests that the network learned to interpret underlying anatomical structures rather than relying on fixed image positioning. Such behavior reflects a critical step toward building intelligent systems that can adapt to real clinical variability.

While these results highlight the effectiveness of the proposed approach, they also open the door for further refinement. Expanding the dataset, incorporating more diverse imaging conditions, and exploring deeper or transfer learning architectures could significantly enhance model robustness and diagnostic precision.

Ultimately, this work reinforces the growing role of deep learning in transforming medical image analysis. The ability of convolutional neural networks to assist in identifying brain tumors demonstrates not only technical progress but also the broader potential of artificial intelligence to support medical professionals in making faster, more informed decisions.

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