Brain Tumor Detection Using Deep Learning: A Binary Image Classification Approach

1. Introduction

Brain tumors are among the most life-threatening forms of cancer, requiring early and accurate diagnosis to improve patient outcomes. Medical imaging, particularly Magnetic Resonance Imaging (MRI), is a critical tool for brain tumor detection and classification. However, manual analysis of these images by radiologists can be time-consuming, prone to human error, and limited by subjectivity. With the growing availability of annotated medical image datasets and advancements in deep learning, automated brain tumor detection systems have the potential to assist clinicians and improve diagnostic accuracy.

This paper presents a deep learning-based binary classification model to detect the presence or absence of brain tumors in medical images. The model is trained on a curated dataset of brain MRI images labeled as either tumor (e.g., glioma) or normal. A convolutional neural network (CNN) is employed to learn hierarchical image features and classify unseen scans accordingly. Data augmentation techniques are applied to increase robustness and reduce overfitting. The performance of the model is evaluated using standard metrics such as accuracy, precision and recall.

2. Methodology

a. Dataset Preparation

The dataset that is going to be used will be the PMRAM: Bangladeshi Brain Cancer - MRI Dataset from Mendeley Data. The dataset consists of brain MRI images divided into two classes: tumor (e.g., glioma) and no tumor (normal). Labels are assigned based on image filenames, and a CSV file is generated to map each image to a binary label (1 for tumor, 0 for no tumor). The dataset is shuffled to ensure class distribution is randomized, and it is then split into training, validation, and testing subsets.

b. Data Preprocessing and Augmentation

To enhance the model's generalizability, data augmentation is applied during training. Transformations include random rotations (up to 45°), horizontal and vertical shifts (up to 20%), zooming (±20%), shearing (20%), and horizontal flipping. Images are resized to a fixed resolution (e.g., 224×224 pixels) and normalized. Empty regions resulting from transformations are filled using nearest-neighbor interpolation.

c. Model Architecture

A pretrained ResNet CNN was used for transfer learning.

d. Training Procedure

The model is trained using binary cross-entropy loss and an optimizer such as Adam. Training is conducted over multiple epochs, with early stopping based on validation loss. Batch normalization and dropout layers are used to prevent overfitting.

e. Evaluation Metrics

The model's performance is evaluated on a separate test set using: accuracy, recall and F1-score.

3. Results and Discussion

The model was trained over 15 epochs with a batch size of 32. Training and validation accuracy steadily increased, while validation loss decreased, indicating that the model successfully learned discriminative features. Early stopping was employed to prevent overfitting based on validation loss. Both accuracy and recall reached 98%. The high recall score is particularly important in medical diagnostics, where false negatives (i.e., failing to detect a tumor) can have serious consequences. The confusion matrix shows that the model made only a few misclassifications, with most errors being false positives (predicting a tumor when none exists).

While the model performs well on the current dataset, it has limitations. It was trained and tested on a single dataset and may not generalize to images from different sources or modalities. The binary classification setting (tumor vs. no tumor) does not account for tumor type or grade, which are crucial in clinical contexts. Future improvements can include: Expanding to multi-class classification (e.g., glioma vs. meningioma vs. pituitary vs. normal) and using explainable AI techniques (e.g., Grad-CAM) to visualize which parts of the image influence the model's decision.

4. Conclusion

This study presents a deep learning-based approach for automated brain tumor detection using binary classification of MRI images. The proposed model demonstrates high accuracy and recall, making it a promising tool for assisting radiologists in early tumor diagnosis. Through data augmentation and proper regularization, the model achieved strong generalization performance on unseen data. Although limited to binary classification and trained on a single dataset, the results indicate that convolutional neural networks are capable of learning meaningful features relevant to brain tumor identification.

Future work will focus on expanding the model to handle multi-class tumor classification, incorporating more diverse and clinically verified datasets, and applying explainability techniques to support interpretability in medical settings. The combination of automation, high accuracy, and fast inference holds potential for supporting real-world diagnostic workflows, especially in regions with limited access to expert radiologists.

5. Citation

Md Shahriar Mannan, Prottoy; Chowdhury , Mahtab ; Rahman, Redwan ; Tamim , Azim Ullah ; Rahman, Md Mizanur (2024), "PMRAM: Bangladeshi Brain Cancer - MRI Dataset ", Mendeley Data, V1, doi: 10.17632/m7w55sw88b.1