Brain Tumor MRI Classification Using Deep Learning

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***Abstract*—This project focuses on the classification of brain tumor images using deep learning techniques applied to MRI scans. The primary objective is to develop a model that accurately identifies the presence of brain tumors. Using a dataset from Kaggle, we leverage Convolutional Neural Networks (CNNs) for feature extraction and classification. The final model is evaluated based on its accuracy, precision, recall, and F1-score, with the goal of achieving a high-performing automated solution for early detection of brain tumors. Such advancements could assist in enhancing diagnostic processes and improving patient outcomes.**

***Index Terms*—brain tumor, MRI scans, classification, convolutional neural network (CNNs), accuracy, precision**

I. Introduction

Brain tumors represent one of the most life-threatening conditions manifesting as abnormal cell growths within the brain. These tumors can be classified as benign (non-cancerous) or malignant (cancerous), with the latter posing a significant risk to life due to their aggressive nature. Early and accurate detection of brain tumors is critical for determining effective treatment strategies and improving patient survival rates.

Magnetic Resonance Imaging (MRI) is the preferred imaging modality for brain tumor detection because it provides high-resolution images that can reveal structural abnormalities in the brain. However, manual interpretation of MRI scans is time-consuming and highly dependent on radiologist expertise, which introduces the potential for human error. With the increasing volume of medical imaging data, automated systems that can classify brain tumors accurately are becoming essential.

Deep learning, a subset of artificial intelligence, has emerged as a powerful tool for medical image analysis, especially in the field of MRI-based brain tumor classification. Convolutional Neural Networks (CNNs), in particular, have demonstrated exceptional capability in identifying intricate patterns and features in medical images, outperforming traditional machine learning approaches. These models learn directly from the raw data, automating feature extraction and classification without the need for manual input.

This study explores the use of deep learning techniques for the classification of brain tumors using MRI scans. By leveraging CNNs, this approach aims to enhance the accuracy of brain tumor detection and classification, ultimately contributing to more timely and precise diagnoses, improving patient outcomes, and minimizing the risk of human error.

Objective:

- To develop a deep learning-based classification model for brain tumor detection using MRI images.
- To train and evaluate the model on a publicly available dataset from Kaggle containing both tumor and non-tumor images.
- To achieve high accuracy, precision, and recall for the classification task.
- To contribute towards developing an automated diagnostic tool that aids radiologists in detecting brain tumors early, potentially saving lives.

The project aims to create a deep learning-based model to classify brain tumors in MRI images, enhancing early detection. Using a Kaggle dataset of tumor and non-tumor images, the model will be trained to achieve high accuracy, precision, and recall. This automated tool will support radiologists, streamlining diagnosis and potentially saving lives.

II. Literature Review

Magnetic Resonance Imaging (MRI)-based automatic brain picture segmentation and classification has been proposed by akter et al. [1] with a deep Convolutional Neural Network (CNN)-based architecture. Using the segmentation strategy, the model achieves an accuracy of 98.8%, while in a merged dataset, it achieves a higher accuracy of 98.7%. Overall, the model surpasses current pre-trained models across all six datasets. Through the use of MRI scan input images, this innovative system may be used in clinics to automatically identify and segment brain cancers.

The goal of elena et al. [2] was to use a ResNet-50 architecture to create an image classification model for brain tumor detection. A dataset of 3847 brain MRI images was used for training, validation, and testing, and the CRISP-DM approach was applied for data mining. Pixels were divided by 255 using a data generator, and the photos were resized to a 255 by 256 scale. The results of the training and assessment procedures were 92% accuracy and 94

The progressive generative adversarial network (SPGAN-MSOA-CBT-MRI) for brain tumor classification on MRI images is presented by nagarani et al. [3] using a self-attention approach. Data preprocessing using anisotropic diffusion Kuwahara filtering (ADKF) is done on data collected from the Brats 2019 dataset. Six features related to texture are extracted, including homogeneity, contrast, inverse difference moment, entropy, correlation, and variance, and are subsequently supplied into the feature extraction segment.

Mohanty et al. [4] presents a deep learning model to enhance the precision of MRI-based brain tumor classification through the application of a soft attention mechanism. The model aggregates and combines information from each layer using a Convolutional Neural Network (CNN) with four convolution layers. By highlighting the characteristics that are most clinically relevant, the soft attention mechanism at the terminal phases improves classification accuracy.

The identical radiographic features and laborious exams associated with brain tumors might make diagnosis difficult. For automatic brain tumor extraction and detection from 2D CE MRI images, an intelligent system is proposed by sahoo et al. [5]. In order to identify extracted tumors using a YOLO2 transfer learning approach, the system is divided into two stages.

Ranjan et al. [6] increased the diagnostic accuracy of brain tumors by using denoising and data augmentation methods to medical images from three different datasets. To assess the efficacy of these techniques, the researchers employed Convolutional Neural Networks (CNNs). [7]The administration of healthcare has improved, while brain tumors remain a leading cause of mortality globally. Essential resources for medical research include databases such as those on pancreatic and brain tumors.

Patients are very concerned about brain tumors because they have the potential to become malignant cells. Improving their quality of life requires early detection and treatment. The most popular technique for finding brain tumors is to use magnetic resonance imaging (MRI) scans. But the procedure is time-consuming and demands image processing knowledge. Because of its success in finding aberrant brain regions, the burgeoning subject of deep learning (DL) machine learning has drawn attention.

Shenbagarajan et al. [8] suggests a brand- new DL and ML-based MRI brain tumor detection technique. The Adaptive Contrast Enhancement Algorithm (ACEA) and median filter are used to preprocess the MRI images before fuzzy c-means segmentation is applied. Features including energy, mean, entropy, and contrast are extracted using the gray-level co-occurrence matrix (GLCM). Combined Deep Neural Support Deep learning has greatly advanced medical knowledge by providing a better grasp of biomechanisms. Shreya et al. [9] focuses on the use of deep learning for brain tumor segmentation, which is a difficult issue because tumor forms and sizes vary widely. In comparison to state-of-the-art models, a novel, straightforward fully convolutional network (FCN) is proposed, which offers competitive performance and faster run-time. The approach is 18 times faster than the state-of- the-art model, achieving dice scores of 0.83 in the total tumor region, 0.75 in the core tumor region, and 0.72 in the enhancing tumor region using the Brain Tumor Segmentation (BraTS) challenge database. Using brain magnetic resonance imaging (MRI) and ma- chine vision techniques, Nawaz et al. [10] sought to create a model for classifying brain tumors. For the categorization of cystic, glioma, meningioma, and metastatic brain tumors,a unique hybrid-brain-tumor-classification (HBTC) framework was created and assessed. The brain tumor diagnosis method performed better and had less inherent complexity thanks to the framework. From the segmented dataset, the input brain MRI dataset was preprocessed, split, and retrieved. The framework's classifiers, which include multilayer perception, J48, meta bagging, and random tree, were trained with the nine best-optimized features. With a maximum brain tumor classification performance of 98.8%, the framework's potential as a cutting-edge and reliable classification framework was evident.

III. Methodology

A. Data Preparation and Augmentation

1) Data Loading: The training and testing data are loaded from specified directories.

2) Data Augmentation: For training data, techniques like rescaling, rotation, zooming, and horizontal flipping are applied to increase dataset diversity and improve model generalization. The test data is only rescaled

B. Model Selection and Modification

1) Transfer Learning Model: ResNet50 pre-trained on ImageNet is used as a base model, which captures general image features.

2) Custom Layers Addition: Custom layers, including a global average pooling layer and dense layers, are added on top of ResNet50 to tailor it to the specific task of tumor classification (four classes).

3) Freeze Base Model Layers: The ResNet50 layers are frozen to retain learned features from ImageNet and focus training on the new dense layers.

C. Model Compilation and Training

1) Compilation: The model is compiled with the Adam optimizer, categorical cross-entropy loss (for multi-class classification), and accuracy as the performance metric.

2) Training: The model is trained on the augmented training data for 10 epochs, validating on the test set after each epoch. The training history (accuracy and loss) is recorded.

D. Evaluation

1) Classification Report and Confusion Matrix: Predictions on test data are evaluated using a classification report (precision, recall, and F1 score) and a confusion matrix, providing detailed performance insights for each tumor class.

2) Additional Metrics: Precision, recall, and F1 scores are also computed to understand the model's balanced performance.

TABLE I
PERFORMANCE MEASURES OF THE CUSTOM CNN MODEL

	precision	recall	f1-score	support
glioma_tumor	0.42	0.11	0.17	100
meningioma_tumor	0.28	0.17	0.21	115
no_tumor	0.29	0.77	0.42	105
pituitary_tumor	0.52	0.15	0.23	74
Accuracy			0.31	394
macro avg	0.38	0.3	0.26	394
weighted avg	0.36	0.31	0.26	394

E. Saving and Reloading the Model and History

1) Model and Training History Saving: Both the model and training history are saved to Google Drive to facilitate future use.

2) Reloading for Predictions: The model is reloaded, and predictions are made on the test set, followed by recalculation of metrics.

F. Convolutional Neural Network (CNN) Model for Comparison

1) CNN Architecture: A custom CNN is also trained as a comparative model to ResNet50, consisting of convolutional layers with max pooling and dense layers.

2) Training and Evaluation: The CNN undergoes similar training, validation, and evaluation steps, allowing for performance comparison between transfer learning and a custom-built CNN model.

IV. Results and discussion

A. Dataset description

The dataset comprises brain MRI images categorized into four classes: glioma tumor, meningioma tumor, no tumor, and pituitary tumor. The training set includes 394 images, while the testing set's size and class distributions are specified in evaluation metrics.

The performance of the both models and their comparison is given in tables IV and II

V. Conclusion

The custom CNN model outperformed the transfer learning approach (ResNet50) with higher validation accuracy (52.5% vs. 31%) and more balanced metrics across tumor classes. Both models struggled with classifying specific tumor types, indicating data limitations or insufficient feature learning. Data expansion and balancing, along with fine-tuning or testing additional architectures, could enhance classification performance. The models require further optimization to achieve clinically reliable results. Overall, the CNN model shows promise but needs improvement for practical application.

This model could assist radiologists in diagnosing brain tumors more efficiently, reducing diagnostic time and aiding early treatment. Future work should focus on expanding the dataset for better generalization, fine-tuning advanced architectures, and exploring multi-label classification for complex cases. Incorporating explainable AI would enhance transparency, showing which MRI areas the model prioritizes. Testing in clinical environments is essential for real-world validation. These improvements would make the model more accurate, interpretable, and ready for practical application.

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TABLE II
PERFORMANCE COMPARISON OF THE MODELS

Model	Training Accuracy	Validation Accuracy	(F1-Score)	Observation
Transfer Learning (ResNet50)	60.39%	31%	Glioma Tumor: 17%, - No Tumor: 42%, Weighted Avg: 26%	Limited generalization on test data. Better recall for ”No Tumor” class, low recall for others.
Custom CNN	81%	52.5%	Glioma Tumor: 30%, Pituitary Tumor: 58%, Weighted Avg: 50%	Improved accuracy and balanced metrics across tumor types compared to ResNet50-based model.

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