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Enhancing Brain Tumor Diagnosis with AI: A Study on MRI Image Analysis

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ABSTRACT:

Brain tumors represent one of the most aggressive and life-threatening forms of tumor, often leading to significant neurological impairments and reduced life expectancy. Early detection and accurate diagnosis are critical for improving patient survival rates and treatment outcomes. Traditional diagnostic methods, such as MRI and CT scans, while effective, rely heavily on the expertise of radiologists and are subject to human error. Recent advancements in artificial intelligence (AI), particularly in machine learning (ML) and deep learning (DL), offer promising avenues to enhance diagnostic precision. This study focuses on developing AI-based diagnostic tools for the early detection and classification of brain tumors using magnetic resonance imaging (MRI).

This study aims to develop an AI-based model that can accurately identify and classify tumor types based on MRI. The system will analyze large datasets of medical images to detect abnormalities, classify tumor stages, and differentiate between benign and malignant growths. The developed AI model promises to improve diagnostic accuracy, reduce false positives and negatives, and provide real-time analysis. Additionally, it seeks to complement the expertise of healthcare professionals by offering a user-friendly interface for medical image processing, ultimately enhancing the decision-making process in clinical settings. Future iterations of this system could integrate further functionalities, such as multi-modal data analysis and predictive analytics for treatment response.

KEYWORDS: Deep Learning, Transfer Learning, CNN, VGG16, ResNET101

1. INTRODUCTION

A brain tumor is a condition brought on by the growth of aberrant brain tissues or cells. Typically, cells divide and die in a predictable order, with each new cell replacing the one before it. But if cells develop abnormally and keep growing, seriously impair brain function and frequently result in death (H. A. Shah et al., 2022). Brain tumor is a common, deadly disease that kills many people, even in wealthy countries. With almost 20,000 people killed by this deadly illness, the death toll in the US is especially concerning (Almufareh et al., 2024). The most frequent tumors in the brain are malignant (C. H. Li et al., 2023) and Gliomas (Gumaei et al., 2019). Malignant brain tumors are identified in 20–40% of tumor patients, with lung tumor accounting for roughly 39% of these cases. Chemotherapy, radiosurgery, and surgery are the common treatment options for brain tumors(C. H. Li et al., 2023). The glia cells in the healthy white matter mutate to produce gliomas(Y. Q. Li et al., 2019) . Glioblastoma tumor treatment fields are authorized adjuvant therapies. It has been demonstrated that the anti-tumoral response is correlated with the strength of the applied electrical field. Nevertheless, peritumoral edema may cause electrical current to be shunted around the tumor, decreasing the intra-tumoral electric field (Lang et al., 2020).

A brain tumor is a condition brought on by the proliferation of aberrant brain cells. It is challenging to estimate the survival rate of a patient with a tumor because they are rare and can take many different shapes. Although MRI is a crucial tool for identifying tumors, manual detection of these tumors is a laborious and difficult process that may result in some inaccurate results(Asif et al., 2022; Chaki & Wozniak, 2023; H. A. Shah et al., 2022). Brain tumors are a serious medical issue that can be difficult to diagnose and treat. One such method for automating the brain tumor diagnostic procedure is deep learning(Zaitoon & Syed, 2023). Deep Learning (DL) methods for brain tumor classification have shown promising results, they are also utilized to address inconsistencies when the visual representation of brain tumor and non-brain tumor regions is equal (Yan et al., 2022). Image classification algorithms usually employ machine learning techniques to identify the typical visual characteristics of each group. By determining which category best fits the visual content of the image(Srivastava & Ahmed, 2021a, 2021b, 2024).

Classifying brain tumor is a crucial stage that relies on the expertise and experience of the doctor. An automated tumor classification system is needed to help doctors and radiologists detect brain tumors. In this study, an automated transfer learning-based model has been developed that can predict whether a person is suffering from a brain tumor or not, and it also indicates the type of brain tumor.

Sr No.	Reference	Findings
1	(Noreen et al., 2020)	Model: Pre-trained Inception-v3, Pre-trained DensNet201 Dataset: Brain Tumor Dataset (Figshare) Accuracy: 99.34% (Inception-v3), 99.51% (DensNet201)
2	(Gumaei et al., 2019)	Model: Extreme Learning Machine (ELM) Dataset: Brain Tumor Dataset (version 5)
3	(Huda et al., 2016)	Model: GANNIGMA + MRMR + Bagging + Decision Tree Dataset: Imbalanced brain tumor dataset Accuracy: Higher accuracies compared to existing algorithms (exact accuracy not specified in the provided context)
4	(H. A. Shah et al., 2022)	Model: Fine-tuned EfficientNet-B0 Dataset: Brain Tumor Dataset (Kaggle) Accuracy: 98.87%
5	(Bibi et al., 2024)	Model: Pre-trained Inception-v4 Dataset: Brain Tumor Dataset (Figshare, SARTAJ dataset, Br35H) Accuracy: 98.7%
6	(Younis et al., 2024)	Model: Pre-trained ResNet50 Dataset: 7,023 MRI images (5712 for training, 1311 for testing) Accuracy: 99%
7	(Almufareh et al., 2024)	Model: YOLOv5, YOLOv7 Dataset: Brain Tumor Dataset (Figshare) Accuracy: 94.7% (YOLOv5 for box detection), 94.1% (YOLOv7 for box detection)
8	(Chaki & Wozniak, 2023)	Model: Deep Brain Incep Res Architecture 2.0 based Reinforcement Learning Network (DBIRA2.0-RLN) Dataset: Brain Tumor Dataset (7023 images) Accuracy: 97.5% (classification), 95.2% (mean Average Precision for image retrieval)
9	(Solanki et al., 2023)	Model: Convolutional Neural Networks (CNN), Dense-Net, Dark-Net Dataset: BRATS 2018 dataset Accuracy: 98.67% (Dense-Net), 96.52% (Dark-Net)
10	(Neamah et al., 2024)	Model: Various deep learning models including CNNs, RNNs, and hybrid models Dataset: MRI datasets from various sources including BRATS 2015, 2017, and 2018 Accuracy: Ranges from 85.95% to 99.7% depending on the specific model and dataset used
11	(Jabbar et al., 2023)	Model: Caps: VGGNet (Hybrid of CapsNet and VGGNet) Dataset: BraTs-2020 and BraTs-2019 datasets Accuracy: 99% (BraTs-2020), 98% (BraTs-2019)
12	(S. M. A. H. Shah et al., 2023)	Model: VS-BEAM (Voting Based Semi-Supervised Bayesian Ensemble Attention Mechanism) Dataset: T1-weighted contrast-enhanced brain MRI dataset (Figshare) Accuracy: 98.91%
13	(Lang et al., 2020)	Model: Finite Element Models Dataset: T1W and T2W images of the ICBM 2009a Nonlinear symmetric template, MRI sequences from two patient-specific models

Sr No.	Reference	Findings
		Accuracy: Not explicitly mentioned
14	(Alqhtani et al., 2024)	Contrast Limited Adaptive Histogram Equalization (CLAHE), diffusion filtering, Fuzzy C-Means (FCM) clustering technique, Support Vector Machine (SVM) classifier
15	(Asif et al., 2022)	Model: Pre-trained Xception, Pre-trained NasNet Large, Pre-trained DenseNet121, Pre-trained InceptionResNetV2 Dataset: MRI-large and MRI-small datasets Accuracy: 99.67% (Xception on MRI-large), 91.94% (Xception on MRI-small)
16	(Farzamnia et al., 2023)	Model: Time Adaptive Self-Organizing Map (TASOM) optimized by the Whale Optimization Algorithm Dataset: Brain Tumor Detection Dataset (Kaggle) Accuracy: Exceeding 98.5%
17	(Y. Q. Li et al., 2019)	PS-OCT (Polarization-Sensitive Optical Coherence Tomography)
18	(Zaitoon & Syed, 2023)	Model: RU-Net2 +, DBT-CNN Dataset: BraTS dataset Accuracy: 99.51% (High-Grade Glioma), 99.28% (Low-Grade Glioma), 98.39% (Tumor Segmentation for HGG), 99.1% (Tumor Segmentation for LGG)
19	(Yan et al., 2022)	Model: SEResU-Net Dataset: BraTS2019 and BraTS2018 Accuracy: 0.9373 (WT), 0.9180 (TC), 0.8758 (ET)
20	(Atha & Chaki, 2023)	Model: Semi-Supervised Brain Tumor Classification Network (SSBTCNet) Dataset: Brain MRI Dataset (7023 images) Accuracy: 94.3% (using all labelled brain MR images from BD2 dataset)
21	(C. H. Li et al., 2023)	Model: Not explicitly mentioned in the provided content. Dataset: Lewis lung carcinoma (LLC) mouse tumor model. Accuracy: Not explicitly mentioned
22	(Zubair et al., 2021)	Model: Sliding Mode Control (SMC), Integral Sliding Mode Control (ISMC), Double Integral Sliding Mode Control (DISMC), Super-Twisting Sliding Mode Control (ST-SMC) Dataset: Not explicitly mentioned Accuracy: Not explicitly mentioned

2. METHODOLOGY

The revolutionary potential of artificial intelligence in medical diagnostics is examined in this study. The goal of the study is to accurately detect and classify brain tumor by analyzing MRI images using cutting-edge AI techniques, especially deep learning models. AI may greatly reduce human error, speed up diagnosis, and increase overall accuracy by automating the process, and providing radiologists and other medical practitioners with vital help. The proposed model is shown in Figure 1.

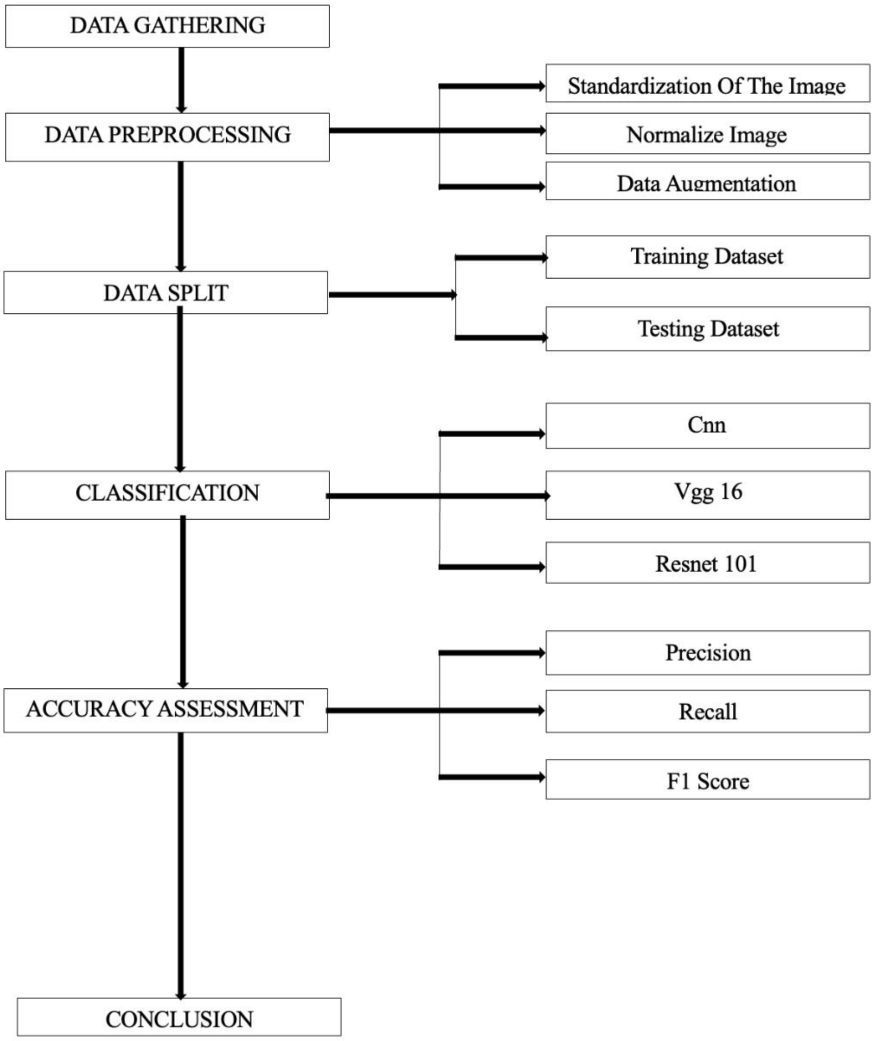

Fig 2.1 Brain Tumor Detection Model Using Transfer Learning

Detailed information about the proposed model is bellowed.

2.1 Data Gathering

The data used to build a model is collected from the Kaggle repository. It contains 7023 MRI images categorized into four categories such as meningioma, pituitary, glioma, and no tumor. Table 1 provides detailed information about the collected dataset.

Sr. No.	Brain Tumor	Sample Size
1	meningioma	1645
2	pituitary	1757
3	glioma	1621
4	no tumor	2000

Table 1 Detailed Information about Collected Dataset

2.2 Data Preprocessing

In this phase, the images are pre-processed to make the original data much more convenient for the development of the deep learning and transfer learning models. Steps which were taken are:

a. Standardization of the image: All the images were resized to specific uniform directions.

b. Normalization of the image: All the images were set on the standardized size of 500 X 500 pixels.

c. Data Augmentation: In the augmentation, multiple operations were performed such as rescaling, and random transformation.

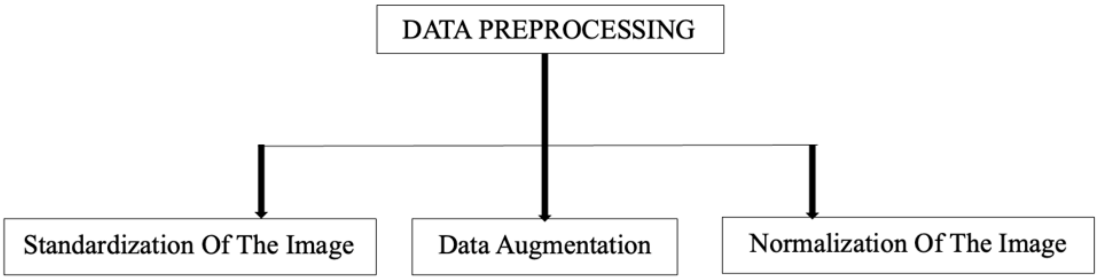

Figure 2.2 Data Preprocessing

2.3 Data Split

The data acquired from the repository is divided into two parts. The first part is used to train the model known as the training sample, and the second one is used to test the model known as the testing sample.

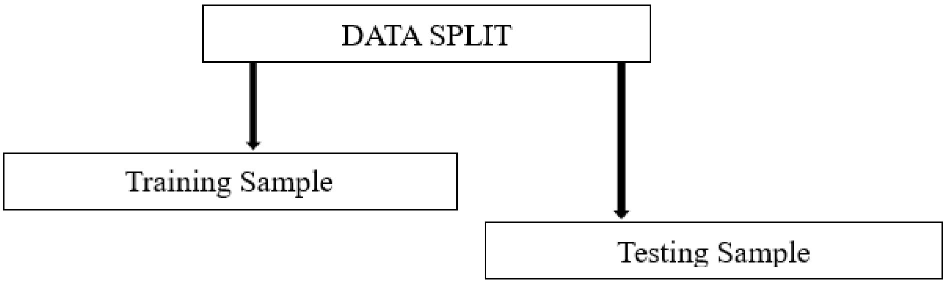

Fig 2.3.1 Data Split

2.4 Classification

Image classification entails utilizing algorithms to group MRI scans into distinct tumor classes. Deep learning and transfer learning-based techniques such as CNN, VGG16, and ResNET101 have been used in the classification of MRI images.

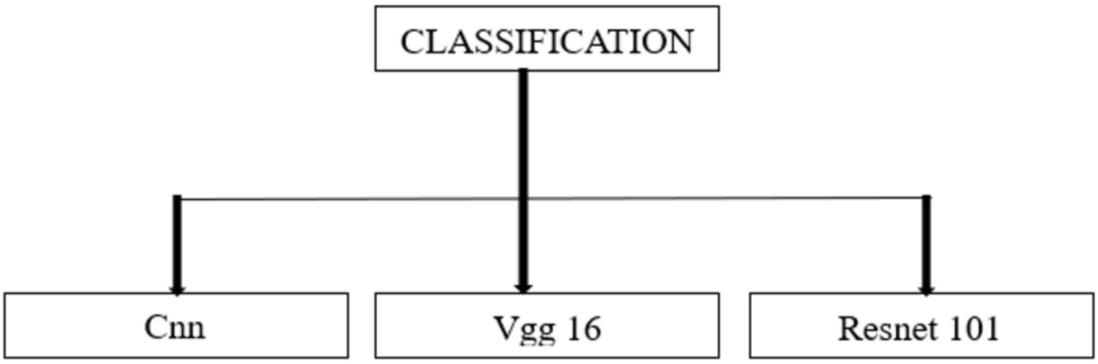

Fig 2.4.1 Image Classification Techniques

a. CNN: A foundation deep learning model used for the model's efficiency for feature extraction, which helps in analyzing the complex pattern inside the MRI data.

b. VGG 16: A deep network and transfer learning model containing 16 weight layers, picked for the model's ability to gather spatial hierarchies and each detail of the images as it has the sequential structure of convolutional layers.

c. ResNET 101: A model of a residual network containing 101 layers, was used to remove the gradient problem common in deep networks by building shortcut connections, helping it to learn more complex patterns in a more deep structure.

2.5 Accuracy Assessment

After the classification, the accuracy was measured of all three models in terms of overall accuracy, recall, precession, and f1 score.

2.6 Discussion

A brain tumor is an out of common growth of the cell inside the brain which can be harmful. There are around 120 types of different brain tumors which can be cancerous and cancerous that is malignant. In our research, the main focus is on 4 types of brain tumors which are meningioma, pituitary, glioma, and no tumor. The detailed information about the dataset is mentioned in Table 1. The sample images of all four categories are shown in Figure 5.

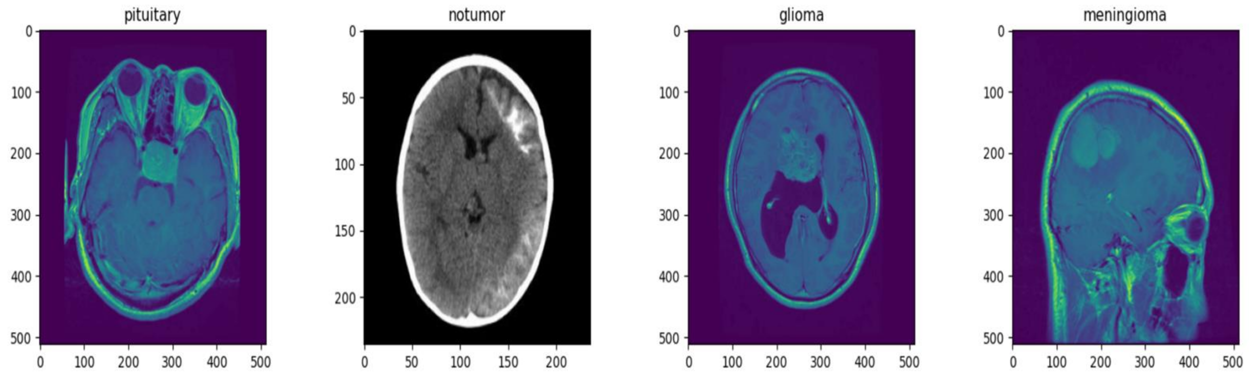

Fig 2.6 Sample Images of Brain Tumor

After the data-gathering process, data pre-processing techniques were applied to make the primary data suitable for the expansion of the transfer learning models. Further in this, steps such as standardization of images i.e. resizing the MRI images in a particular steady way, normalization of images i.e. all the MRIs set to the same standard pixels of 500 X 500, and other data augmentation techniques were applied as rescaling, random transformation.

After the data pre-processing, the dataset was separated into two subsets, the first one used for training the model which contains 5712 images, and the second one used for testing which contains 1311 images. Detailed information about training and testing samples are mentioned in Table 2.

Sr. No.	Sample Type	Brain Tumor Types			
		Meningioma	**Pituitary**	**Glioma**	**No Tumor**
1	**Training**	1339	1457	1321	1595
2	**Testing**	306	300	300	405

Table 2 Detailed information about training and testing samples

After the splitting of data, By using these high-quality MRI images, three models were trained efficiently to perform the accurate classification. The models were trained and tested by CNN, VGG 16, and RESNET101. The obtained results are mentioned in Table 3.

Sr. No.	Classifiers	Accuracy		Average Precision	Average Recall	Average F-1 Score
		Train	**Test**			
1	**CNN**	99.43%	97.483%	0.975	0.9725	0.9725
2	**VGG 16**	99.82%	99%	0.99	0.99	0.99
3	**ResNET 101**	99.67%	98.703%	0.9875	0.985	0.985

Table 3 Obtained Results from CNN, VGG, and ResNET101 Classification

It can be observed from the table, that the VGG 16 is producing better results to compare than the CNN and ResNET 101 in terms of accuracy, precision, recall, and f1 score so the VGG 16 model can be used in the application of brain tumor detection.

3. CONCLUSION

This study demonstrates the revolutionary potential of artificial intelligence in improving MRI image analysis for brain tumor identification. The study shows notable increases in the accuracy of tumor identification and classification by utilizing cutting-edge deep learning and transfer learning techniques. AI integration represents a major advancement in neuro-oncology therapy since it reduces diagnostic errors and offers useful support for individualized treatment plans. Notwithstanding the encouraging outcomes, issues like the requirement for reliable datasets, the interpretability of AI models, and clinical validation are still crucial topics for further research. However, this study establishes the foundation for a wider use of AI in medical imaging, intending to transform diagnostic procedures and enhance patient outcomes in the battle against brain tumors.

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