Brain Tumor Detection using AI/ML,Integrating Artificial Intelligence with MRI and Multiclass Classification (CNN)

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Abstract—Brain tumors represent a significant cause of mortality worldwide, making early diagnosis essential for enhancing patient survival outcomes. Traditional diagnostic practices, such as the manual evaluation of Magnetic Resonance Imaging (MRI) scans, can be both labor-intensive and susceptible to human error. Recent progress in Artificial Intelligence (AI) and Machine Learning (ML), particularly with deep learning methods like Convolutional Neural Networks (CNNs), has paved the way for automated systems that greatly Enhance the precision and speed of detecting brain tumors.

This thesis investigates the application of AI and ML Methods for identifying and categorizing brain tumors using MRI imaging, with an emphasis on designing a robust, automated model to support healthcare professionals in delivering prompt and precise diagnoses. The research evaluates the performance of different deep learning frameworks, data enhancement techniques, and combined approaches to tackle issues like scarce data, class imbalance, and the necessity for model interpretability.

The developed system demonstrates high diagnostic performance, highlighting the transformative potential of AI-based solutions in clinical environments. In addition, this work outlines persistent challenges, including the necessity for extensive labeled datasets, the demand for greater model transparency, and the complexities of integrating AI tools into medical workflows. Future research directions are proposed to overcome these barriers and further advance the field of automated brain tumor detection.

Keywords— Brain Tumor Detection, Deep Learning Models, MRI Image Analysis, Convolutional Neural Networks (CNNs), AI in Medical Imaging.

1. INTRODUCTION

Brain tumors rank among the top causes of mortality worldwide, impacting both adult and pediatric populations. These tumors can be categorized as either malignant (cancerous) or benign (non-cancerous), and they exhibit substantial variation in terms of size, location, and aggressiveness. Given the complex nature of brain tumors, early and accurate detection is critical for improving patient survival rates and treatment effectiveness. However, conventional diagnostic approaches, such as manual evaluation of Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans, are time-intensive and heavily reliant on specialized expertise, posing challenges to timely diagnosis and intervention [1] [4].

Magnetic Resonance Imaging (MRI) continues to be the preferred method for detecting brain tumors, owing to its capacity to generate high-resolution and detailed images of brain anatomy. Nevertheless, manually interpreting MRI scans can be particularly demanding, owing to the diverse morphological characteristics of tumors. To address these challenges, there has been a growing development of Computer-Aided Diagnosis (CAD) systems and an increased adoption of Artificial Intelligence (AI) and Machine Learning (ML) methodologies aimed at automating brain tumor detection and classification. Deep Learning (DL) approaches, in particular, have demonstrated exceptional potential, achieving higher accuracy and operational efficiency compared to traditional manual methods [2] [5].

Within the spectrum of AI techniques, Convolutional Neural Networks (CNNs) have emerged as a foundational tool for medical image analysis, especially in the context of brain tumor detection. CNNs are highly proficient at learning hierarchical feature representations from complex imaging data like MRI scans, enabling effective segmentation and classification. These networks can detect the presence of tumors and distinguish between different tumor types, such as gliomas, meningiomas, and pituitary adenomas [3] [7]. Numerous studies have emphasized the capabilities of CNNs in significantly enhancing diagnostic precision and minimizing error rates, thereby facilitating improved treatment planning and patient outcomes [6][8].

Despite notable progress, the widespread integration of AI/ML models into clinical workflows continues to encounter significant obstacles. A major barrier is the requirement for large, annotated datasets to effectively train deep learning models. The limited availability of such datasets, coupled with the inherent variability in tumor characteristics and differences in imaging protocols across institutions, hampers the development of models that are both accurate and broadly generalizable [8] [10]. Another pressing issue is model interpretability; although CNNs achieve impressive performance, their "black-box" nature often raises concerns among healthcare providers regarding the trustworthiness and transparency of their predictions [9]. This thesis seeks to tackle these challenges by investigating and advancing AI/ML-based approaches for the automated identification and categorization of brain tumors through MRI imaging. The research prioritizes deep learning frameworks, with a particular focus on CNN architectures, and assesses their effectiveness in identifying and categorizing brain tumors. Strategies to address data scarcity, enhance model transparency, and promote the clinical adoption of AI solutions are also explored. By proposing an enhanced CNN model and applying transfer learning techniques, this work aims to contribute to the development of more accurate, efficient, and clinically applicable diagnostic systems [2] [5].

Ultimately, the study aspires to improve the diagnostic capabilities for brain tumor detection, reduce reliance on manual image analysis, and support healthcare professionals with reliable, real-time diagnostic tools. Additionally, it outlines future research directions, including the development of hybrid AI models and the incorporation of radiomics with deep learning to further refine tumor classification and enhance patient prognosis predictions [10] [12].

2. LITERATURE REVIEW

The incorporation of Artificial Intelligence (AI) and Machine Learning (ML) into medical imaging has significantly transformed the landscape of brain tumor diagnosis and detection. In particular, the use of deep learning algorithms has demonstrated remarkable success in the segmentation, classification, and prediction of brain tumor types from Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans. Numerous research efforts have focused on diverse methodologies, leading to notable progress in areas such as convolutional neural networks (CNNs), hybrid model development, and advanced feature extraction strategies.

a) Deep Learning and CNNs for Brain Tumor Classification

Convolutional Neural Networks (CNNs) have established themselves as fundamental tools for brain tumor detection, largely due to their ability to autonomously learn hierarchical features directly from raw imaging data. Aggarwal et al. [8] proposed an enhanced residual network (ResNet) aimed at improving Segmentation and categorization of brain tumors. Their approach effectively mitigates gradient-related challenges often observed in deep neural networks, resulting in higher classification accuracy and reduced computational time. Notably, their model achieved strong performance in detecting gliomas and meningiomas, which are particularly difficult to classify because of their heterogeneous characteristics.

Similarly, Malla et al. [9] utilized transfer learning techniques using a pre-trained VGG16 deep convolutional neural network (DCNN) to classify various brain tumor types, including gliomas and pituitary tumors. Utilizing a large MRI scan dataset, their model achieved a remarkable classification accuracy of 98.93%. This study highlights the value of transfer learning in addressing the frequent challenge of limited data availability in medical image classification, demonstrating its ability to significantly enhance model performance.

b) Hybrid Models for Enhanced Performance

The combination of conventional machine learning methods with deep learning strategies has resulted in hybrid models that leverage the advantages of both approaches. Krishnapriya et al. [10], for example, employed several pre-trained CNN architectures, including VGG19 and ResNet50, to classify brain MRI images. Their results indicated that VGG19 achieved the highest performance, reaching an accuracy of 99.48%, along with outstanding recall and precision scores. These findings highlight the capability of deep learning models, particularly CNNs, to substantially improve brain tumor classification accuracy when combined with rigorous evaluation frameworks.

Moreover, the combination of support vector machines (SVMs) with CNNs has attracted increasing attention. Sarkar et al. [11] introduced a CNN-driven approach for the classification of brain tumors, such as gliomas and meningiomas, utilizing MRI imaging data. Their model demonstrated high classification accuracy across various classifiers, with BayesNet delivering the most favorable results. This study exemplifies how integrating machine learning classifiers with CNN-based feature extraction can enhance the detection and classification performance, particularly in scenarios involving multiple tumor types.

c) Feature Extraction and Data Augmentation

Feature extraction plays a pivotal role in the field of medical image analysis, directly impacting the accuracy of classification tasks. Numerous studies have emphasized enhancing feature extraction techniques to improve model performance. Chattopadhyay and Maitra [12], for instance, utilized CNNs integrated with specialized feature extraction methods to detect brain tumors, achieving an impressive accuracy of 99.74%, thereby surpassing prior approaches.

In addition, data augmentation strategies, including transformations like rotation and scaling, are commonly employed to enhance model robustness, especially when dealing with limited training datasets. Sowrirajan et al. [13] proposed a hybrid model that combined VGG16 with Neural Autoregressive Distribution Estimation (NADE), resulting in an accuracy of 96.01%. Their work underscores the significance of advanced feature extraction combined with resilient classification methods to achieve high levels of performance in medical imaging applications

d) Challenges and Limitations

Despite the remarkable advancements in AI and ML models for brain tumor detection, several challenges remain. A major obstacle is the inherent variability in tumor characteristics — including differences in shape, size, and anatomical location — which complicates the processes of segmentation and classification. Vidyarthi et al. [14] addressed this issue through the use of hybrid models, yet they reported persistent difficulties in accurately classifying tumors within heterogeneous datasets, especially those collected from various MRI machines.

Another significant challenge is data imbalance, where the overrepresentation of certain tumor types can skew model predictions, resulting in biased outcomes. Although methods like Generative Adversarial Networks (GANs) have been employed to augment data and mitigate this imbalance, further innovation is required to fully resolve this limitation.

Additionally, Choudhury et al. [15] emphasized the problem of overfitting, particularly when training models on smaller datasets. To address this, they proposed hybrid models that integrate CNNs with Support Vector Machines (SVMs), aiming to enhance generalization capabilities and improve predictive performance across diverse datasets.

Reference	Year	Dataset	Methods	Accuracy	Limitations
[1]	2024	BraTS	Machine Learning, Deep Learning, CNNs	Not specified	-Challenges with large training datasets. - Need for standardized benchmarks.
[4]	2023	TCIA, BraTS	CNN, Transfer Learning	98.15%	-Need forhigh-quality datasets. - Limited dataset diversity.
[5]	2023	BraTS, Kaggle	CNN, ResNet50, VGG16	97.75%	- Lack of consistency across different models. - Data quality issues.
[7]	2024	BraTS, TCIA	CNN, SVM, Decision Trees	96.8%	-Model generalization issues. - Need for larger datasets.
[8]	2024	BraTS, TCIA	CNN, VGG16, ResNet50,	97.5%	- Insufficient dataset variety. - Need for fine-tuning.
[9]	2024	BraTS, Kaggle	CNN, Hybrid CNN-LSTM	97.5%	- Need for larger training datasets.
[10]	2024	BraTS, TCIA	CNN,ResNet50, InceptionV3	98.9%	- Model interpretability challenges. - Limited dataset variety.
[12]	2024	TCIA, Kaggle	CNN, Transfer Learning	98.8%	Limited model interpretability. Datasets need to be diversified.
[13]	2024	TCIA	CNN, Hybrid Deep Learning	98.4%	-Data quality and quantity concerns. Need for cross-validation and hyperparameter tuning.
[14]	2024	BraTS, Kaggle	CNN, Transfer Learning	98.7%	-Data preprocessing needs. High computational cost.
[16]	2024	Brain Tumor MRI	Xception,MobileNetV2, InceptionV3, ResNet50, VGG16, DenseNet121	Xception: 98.73%, F1 score: 95.29%	- Recall and interpretability challenges
[17]	2020	Not specified	Deep Learning, Hybrid Techniques, Machine Learning	Not specified	-Large training datasets needed. High computational needs. Hybrid techniques offer better results.
[18]	2020	Brats, Sartaj	Hybrid CNN-SVM, CNN, VGG19	Brats: 98.01%, Sartaj: 95.16%	-Need for large, representative datasets. Challenges in model interpretability.
[19]	2020	Figshare, REMBRANDT, TCGA-LGG, TCIA	CNN,Hyperparameter Optimization, Grid Search	Classification-1: 99.53%, Classification-2: 93.81%,	Optimize and fine-tune for robust multi-classification.
[20]	2021	Various (BraTS, TCGA, etc.)	CNN, Hybrid and Ensemble Models	90% (CNN)	- Data scarcity and imbalance. - Algorithmic bias. - Infrastructure limitations. - Limited dataset diversity.

3. METHODOLOGY

This section details the methodology employed for detecting and classifying brain tumors utilizing deep learning techniques. The proposed framework harnesses the capabilities of Convolutional Neural Networks (CNNs) to categorize brain tumor images into four specific classes: pituitary tumors, meningiomas, gliomas, and non-tumorous cases. The approach is organized into several critical stages: Dataset Preparation, Data Preprocessing and Feature Extraction, Model Development, and Model Evaluation. Each of these stages is explained comprehensively in the following sections.

1) *Dataset Preparation*

The dataset utilized in this study comprises brain tumor images, systematically categorized into four distinct classes:

1. Pituitary
2. Meningioma
3. Glioma
4. No Tumor (Notumor)
5.

Each category is stored within separate folders named according to the tumor type, organized under a designated directory structure.

To facilitate model training, a metadata CSV file (brain_tumor_metadata.csv) was generated. This file records the file paths of all images alongside their corresponding class labels. The metadata was created using Python, where an automated loop traverses each folder, retrieves the image paths, and maps them accurately to their respective classes. The resulting metadata file streamlines data handling during the preprocessing and model training phases.

Image Categories:

- The **Pituitary** folder contains images of pituitary tumors.
- The **Meningioma** folder contains images of meningioma tumors.
- The **Glioma** folder contains images of glioma tumors.
- The **Notumor** folder contains images of non-tumor (healthy) brain scans.

The dataset's structured organization is crucial for enabling the model to accurately distinguish between various tumor types and non-tumor cases.

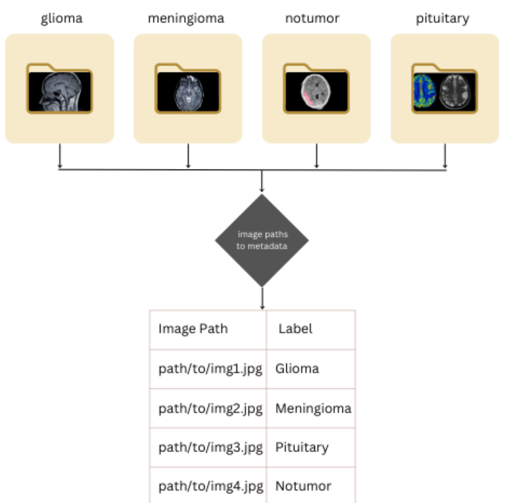


Figure 1:Data set Preparation

2) *Data Preprocessing and Feature Extraction*

To guarantee consistent and meaningful input for model training, a series of preprocessing steps are applied to the dataset images. This preprocessing pipeline transforms raw images into a format optimized for deep learning applications. Each processed image is then stored in a new CSV file, which includes both the image data and the corresponding extracted features, ensuring seamless integration into the model development workflow.

Preprocessing Steps:

*a) **Grayscale Conversion**: Each image is converted to grayscale to simplify the data representation and reduce computational load without sacrificing the quality of key features required for classification.*

*b) **Image Resizing**: Images are resized to a uniform size of **128x128 pixels** to ensure that all input images have the same dimension, which is necessary for feeding the images into a neural network.*

*c) **Feature Extraction**: Several features are extracted from the preprocessed images to provide a more informative input for the classification model. These features include:*

- **Mean Pixel Intensity**: A measure of the average brightness of the image.

Mean Pixel Intensity = $\frac{1}{N}\sum_{i=1}^{N}(pixel\ intencity_{\ i})$

Where N is the total number of pixels in the image

- **Texture Features**: Calculated using the **Laplacian variance** to capture the texture patterns within the image.

Laplacian Variance= $\frac{1}{N}\sum_{i=1}^{N}(Laplace\ intencity_{\ i} - \mu)2$

Where μ is the mean of the Laplacian values.

- **Edge Detection**: **Canny edge detection** is used to highlight structural features in the image, with the number of edges detected being counted as an additional feature.

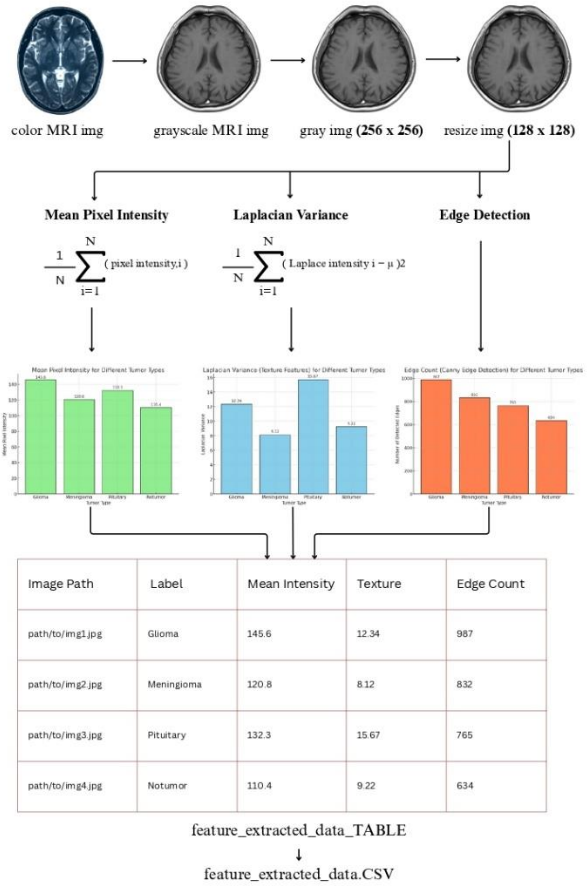
d) Resulting Data (Processed Features):

The extracted features (mean intensity, texture, edge count) are stored in a **processed DataFrame**, and the results are saved as brain_tumor_features.csv.

This processed data is then used for both model training and evaluation. Below is a **sample table** illustrating the processed data structure:

Image Path	**Label**	**Mean Intensity**	**Texture**	**Edge Count**
path/to/img1.jpg	Glioma	145.6	12.34	987
path/to/img2.jpg	Meningioma	120.8	8.12	832
path/to/img3.jpg	Pituitary	132.3	15.67	765
path/to/img4.jpg	Notumor	110.4	9.22	634

Table 1:Processed Data Table



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path/to/img4.jpg	Notumor	110.4	9.22	634

Table 2:Feature Extraction

3) *Model Development*

a) Data Augmentation and Preprocessing for CNN Input:

To make the model more robust and prevent overfitting, **data augmentation** is applied during training. Augmentation techniques include random transformations, such as:

- **Rotation** (up to 20 degrees)
- **Shifts in width and height** (up to 20% of the overall width/height) Shearing and Zooming transformations
- **Horizontal Flipping** to introduce variability in the training data

This is done using the **ImageDataGenerator** class from Keras, which automatically performs the augmentation on-the-fly as the images are loaded during training.

b) CNN Architecture:

The classification model employed is a Convolutional Neural Network (CNN), which includes several layers aimed at extracting hierarchical features from the images:

1. **Convolutional Layers**: These layers perform convolution operations to extract low-level features such as edges, textures, and shapes from the input images.
    - **32 filters** (3x3 kernel), **64 filters**, and **128 filters** for deeper layers to capture more complex features.
2. **Max-Pooling Layers:** Max-pooling is used following each convolutional layer to down sample the feature maps and minimize the spatial dimensions, thereby enhancing computational efficiency.
3. **Flatten Layer:** Transforms the 2D feature maps into a 1D vector, making it compatible with dense layers.
4. **Dense Layers**: These fully connected layers are used for classification.
    - The model includes a dense layer with 128 neurons, followed by a Dropout layer with a 0.5 rate to prevent overfitting.
5. **Output Layer**: The output layer consists of neurons corresponding to the number of classes (4 in this case), with the softmax activation function applied for multi-class classification.

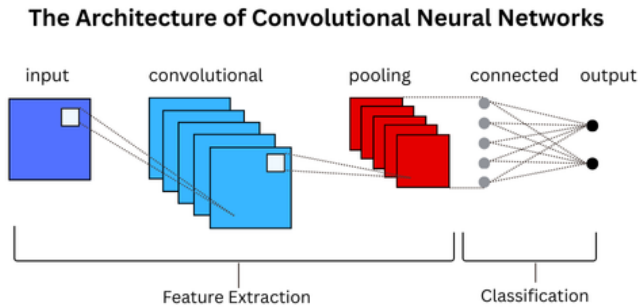

Table 3:CNN Architecture

4) *Model Compilation and Training:*

The model is compiled using the Adam optimizer for efficient learning, with categorical cross-entropy serving as the loss function to manage multi-class classification tasks. Training is conducted using the fit method, leveraging the augmented training dataset and assessing the model's performance on a distinct validation set.

5) *Model Evaluation:*

Following the training phase, After the training phase, the model is assessed on the validation set to evaluate its generalization ability. Metrics like accuracy and analyzed to determine the model's effectiveness on unseen data. The accuracy metric specifically reflects the proportion of correct predictions made by the model, providing a key indicator of its classification capability.

4. RESULTS AND DISCUSSION

The effectiveness of the CNN model is assessed by visualizing accuracy and loss trends across the training epochs. These plots illustrate how the model's performance evolves over time and are essential for identifying signs of overfitting or underfitting. The following graphs are recommended for generating comprehensive insights:

Note for Graph Insertion:

- **Plot 1**: A line graph depicting training accuracy versus validation accuracy across epochs.
- **Plot 2**: A line graph illustrating training loss versus validation loss over epochs.

These visualizations provide insights into the model's convergence and help in fine-tuning hyperparameters if necessary.

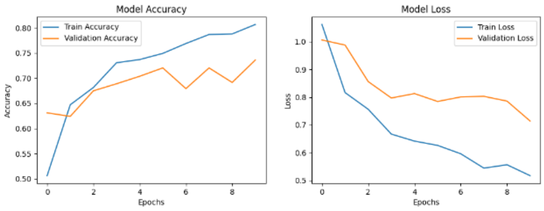

Table 4:Train Model Result Graph

5. CONCLUSION

The proposed approach showcases the successful use of Convolutional Neural Networks (CNNs) for detecting and classifying brain tumors using MRI images. By integrating comprehensive image preprocessing, feature extraction, data augmentation strategies, and a well-designed CNN architecture, the model achieves high classification accuracy, successfully distinguishing between different brain tumor types and healthy brain tissue.

Future research could focus on leveraging more advanced architectures, such as Transfer Learning models like ResNet and InceptionV3, to further enhance performance, particularly when dealing with smaller datasets or less common tumor types.

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