Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606
Volume 07 Issue 02
2024

Research Article
https://doi.org/10.56979/702/2024

Deep Learning-Based Brain Tumor Detection

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Received: May 02, 2024 **Accepted:** August 20, 2024 **Published:** September 01, 2024

Abstract: One of the main causes of death in the globe is brain tumors. Medical image has recently advanced significantly in both case methodologies and applications, enhancing its effectiveness in healthcare management. The brain tumor and pancreatic tumor databases, yield the most accurate and comprehensive results and are crucial resources in medical research. In terms of efficiency, precision, creativity, and other factors, these strategies improved performance. This dataset was preprocessed before being used to assess how well deep learning models identified and categorized brain cancers. Gliomas of low grade, categorized as grades I and II are often treatable through complete surgical removal. Conversely, grade I gliomas of high grade III and IV usually necessitate additional treatment with radiation. The accuracy of the proposed model yields highly effective results, achieving a performance of 96% accuracy. Secondly, the tumor is classified using an enhanced thresholding method informed by the binomial mean, variance, and standard deviation. To highlight the performance of the suggested framework and the novelty of the method are rigorously contrasted with accepted techniques. On the other hand, both geometric features and four texture attributes are obtained. These features are then combined using a step-by-step process, and the optimal features are selected using a Genetic Algorithm (GA).

Keywords: Brain Tumors; Glioma; Image Processing; Malignant; Magnetic Resonance Imaging; Segmentation.

1. Introduction

Brain tumors represent a disease that affects a large number of people, often with life-threatening consequences [1]. The human body typically controls cell increase and reproduction by producing new cells via the processes of cell division [2]. Initial diagnosis disease of brain tumor leads to reduce the seriousness of the condition and lower mortality rates. It is characterized by the body's unchecked cell division and proliferation, which raises the pressure inside the skull on the brain and has a detrimental effect on general health. Normal tissues may sustain harm from brain tumors, and they may spread to other body areas. Indication of the disease fluctuates based on the size of the tumor. There are around 100 distinct types of primary brain tumors known to exist, including one million Americans who are presently suffering from a brain tumor, according to the NBTS [3]. Gliomas, including astrocytic tumors and glioblastomas, rank among the most prevalent types of tumor. Primary cancers of the brain, such as those originating within the brain, generally remain localized to that area [4]. Secondary brain tumors develop when cancer cells invade the brain from the outside [5].

Segmentation plays a major role in detecting tumors in human organs [6]. Many conventional methods such as [7-8], are not efficient. Conventional machine learning-based approaches have shown remarkable performance in complex problems such as [9], however, deep learning approaches outperform as they provide automatically optimized feature extraction.

Brain tumors are categorized in two steps the first is Malignant and the other one is Benign [10]. Malignant tumors can penetrate nearby tissues and proliferate, causing additional tumors to grow in distant body parts. Brain malignancies can be classified into over a hundred types based on location and development characteristics. Doctors categorize brain malignancies as Grades, I, II, III, or IV depending on their growth rate and symptom severity present in Fig. 1.

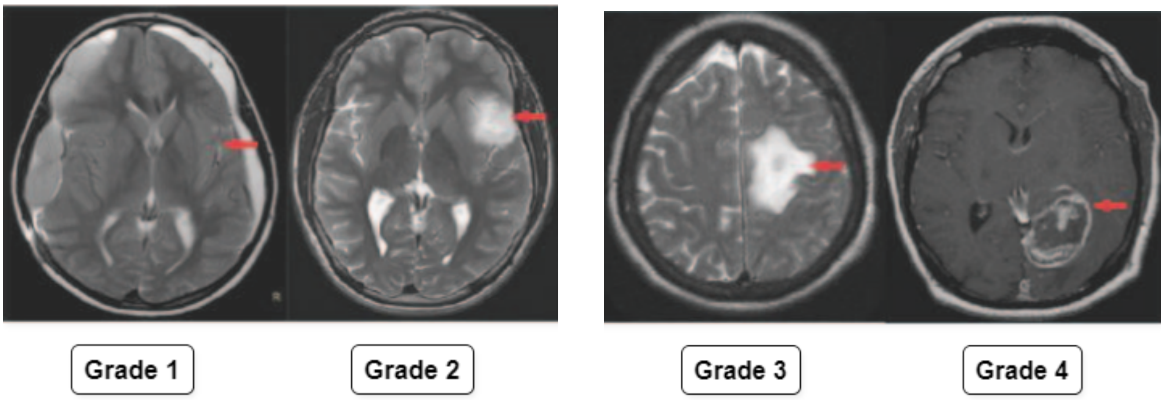

Figure 1. Grade of Astrocytoma in Brain Tumors

The American Brain Tumor Association claims that [11], brain tumors are classified on a scale from grades. Low-grade gliomas of grades I and II generally grow slowly and are benign, whereas gliomas of upper grades III and IV are malignant and exhibit rapid growth tendencies present in Fig. 2. On the other hand malignant tumor, benign tumors can be biopsied safely and do not spread to other organs. Examples of primary brain cancers are pituitary tumors, meningiomas, and gliomas, with glioma being a specific type of neural malignancy that can develop present in Fig. 3. In contrast, brain tumors remain localized and do not spread to other parts of the body. After surgical removal, benign typically do not recur, as opposed to cancerous tumors. Periodically, they can grow to a considerable size, produce intense symptoms, or provide potentially fatal dangers. Abnormal cell growth leads to specific forms of brain tumors, such as pituitary tumors, gliomas, and meningiomas. Meningiomas commonly originate in the thin membranes that develop the brain and are predominantly non-cancerous. Despite being mostly benign, meningiomas can still pose significant health risks and have a direct impact on human life. This represents the fundamental difference between these three types of malignancies. Pituitary tumors, though generally benign, can cause significant medical complications and challenges. Moreover, tumors may develop as abnormal masses around the pituitary glands at the skull's base. These tumors can impact multiple biological systems.

This marks a critical turning point in the management of brain cancers and depends on a comprehensive understanding of the various stages of the disease. Radiologists employ various imaging modalities, such as CT, PET, and Magnetic Resonance Imaging (MRI) scans to look for brain tumors and assist in precise diagnosis and selecting suitable treatments in current years [12]. The brain structure is analyzed utilizing a computed tomography (CT) scan or magnetic resonance imaging (MRI) scan. When it comes to illness diagnosis, MRI scans are noticeably superior to CT scans, and they pose no risk of radiation exposure to the human body, relying instead on magnetic fields and radio waves for imaging Because magnetic resonance imaging (MRI) offers accurate and dependable segmentation of the affected areas, it is utilized to detect brain malignancies. Extracting detailed and relevant features from MRI images allows for precise prediction of brain tumor characteristics. Clustering allows for reliable identification of tumor size, which in turn enables more effective treatment and reduces the risk of mortality associated with brain tumors [13]. Pixels with similar characteristics are clustered into distinct regions, separated from those with dissimilar characteristics. Examining the results of an MRI requires careful monitoring and a high degree of competence, which exceeds the capability of an ordinary person. Unfortunately medical facilities, including hospitals, still lack the knowledge needed to meet these standards, which prolongs the diagnostic process.

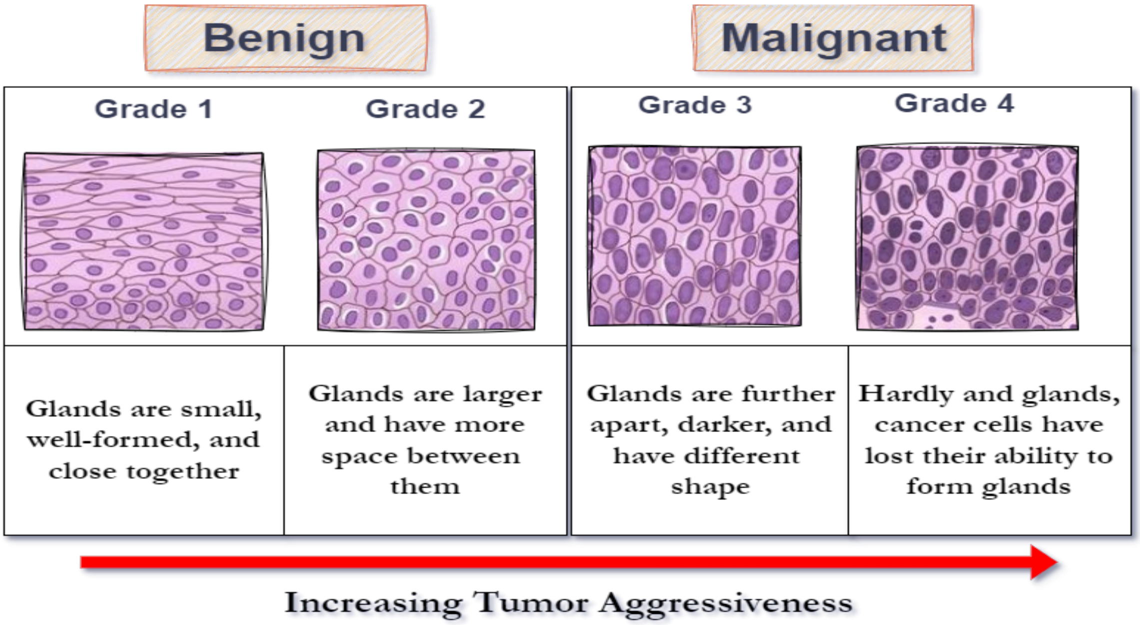

Figure 2. Four Different Types of Brain Tumor Grade

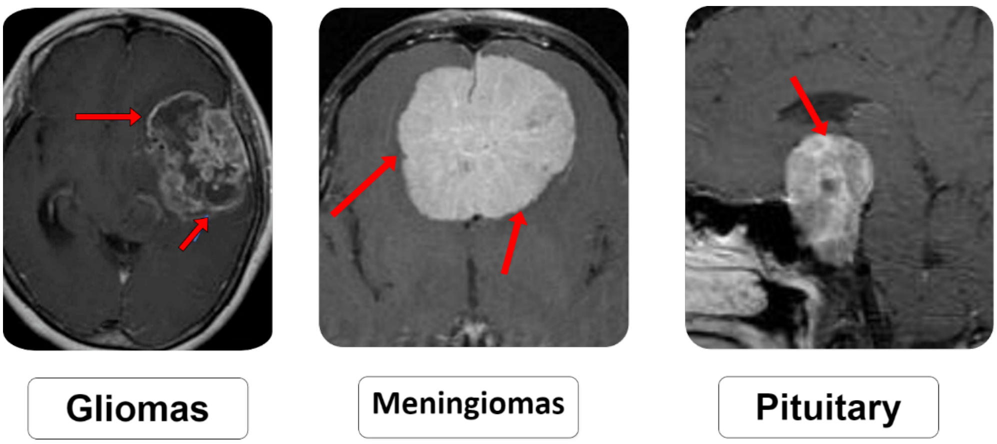

Figure 3. Type of Primary Brain Tumors

Patients diagnosed with grade II gliomas are typically advised to undergo regular assessment with scans every six months to a year for an MRI or CT scan. Complete surgical excision is often the only treatment available for low-grade gliomas (grades I and II), whereas high-grade III and IV that are malignant typically require treatment using chemotherapy, radiotherapy, or a mix of both. Glioblastoma, is the most aggressive type of astrocytoma, which is classified as a grade IV tumor and is characterized by necrosis and fast blood vessel development. Within this categorization, glioblastomas are the most malignant tumors with the quickest growth rate. Accuracy in medical imaging depends on proper segmentation. Tumor tissue identification by partitioning a picture into parts or sections that share similar attributes such as grayscale levels, contrast, color, and texture.

1.1. Glioma

One kind of brain tumor that develops from the brain's supporting Glial cells is called a glioma. Gliomas are categorized into different types, including astrocytomas, oligodendrogliomas, and ependymomas, depending on the particular glial cells from which they come. Extensive growth and resistance to treatment present significant challenges in managing and treating these tumors present in Fig.4.

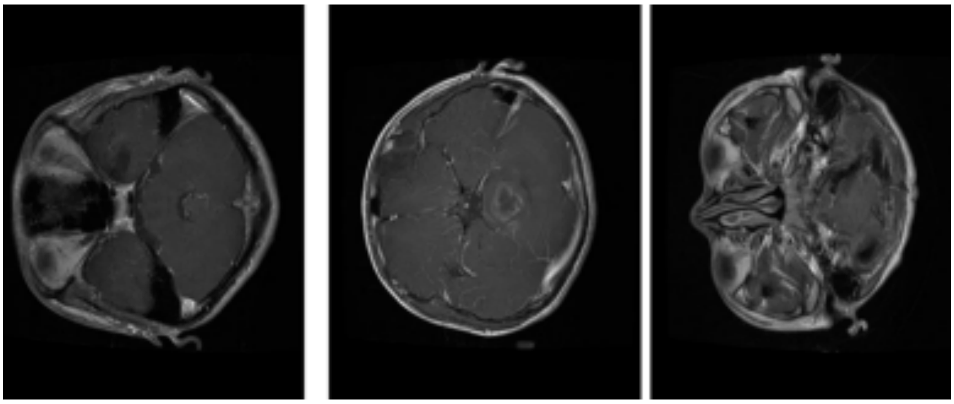

Figure 4. MRI Image Classes i.e., Glioma.

1.2. Meningioma

One kind is a brain tumor which starts in the layers of tissue within the meninges that surround the brain and spinal cord and is called a meningioma. Depending on their size and location, these tumors can cause symptoms, although they usually grow slowly and are benign. A meningioma may form along the meninges' surface and exert pressure on nearby brain regions, potentially causing a variety of neurological manifestations. Meningiomas are often treated with surgery, and this is typically associated with a favorable prognosis as shown in Fig.5.

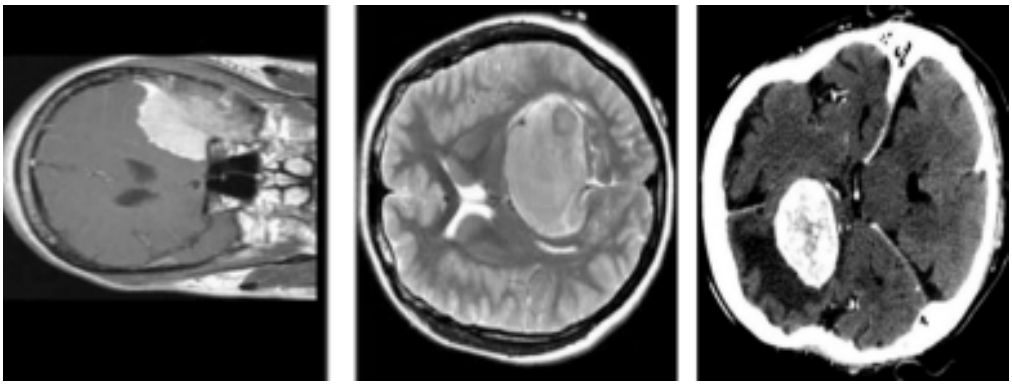

Figure 5. MRI Image Classes i.e., Meningioma

1.3. Pituitary

The pituitary gland is a little gland located close to the base of the brain that regulates hormone release, and pituitary tumors grow. These tumors may interfere with normal hormone levels and might be benign or cancerous. Pituitary tumors can induce hormonal imbalances that impact different body systems, depending on their size and hormonal activity. Common types include non-functioning adenomas, growth hormone-secreting tumors, and prolactinomas. Alternatives for treatment, which seek to relieve symptoms and restore hormonal balance, include radiation therapy, medicine, or surgery as seen in Fig.6.

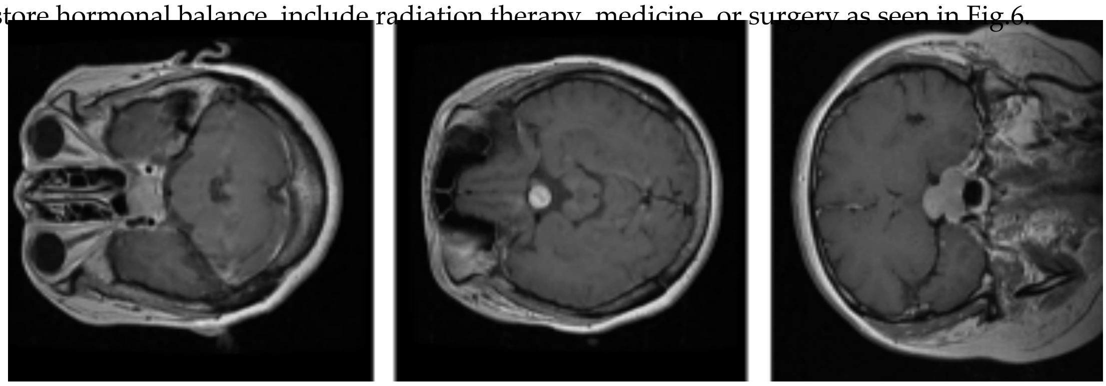

Figure 6. MRI Image Classes i.e. Pituitary

2. Literature Review

This segment analyzes the content of exciting research on brain tumor categorization and segmentation. As advanced research progresses, computer vision is increasingly valuable in medical research and Analysis of health issues. Shaf et al. (2021) [14] employed a combined approach using MRI, including gliomas, meningioma, and pituitary. This method involves the stages of preprocessing, feature classification, extraction, and selection. Develop a dependable model for glioma brain tumor diagnosis using a Magnetic Resource Imaging-based (MRI) classification scheme. This author Dang et al. (2022) [15] aims to resolve this by creating a dependable model for diagnosing brain tumors called gliomas using a magnetic resonance imaging-based categorization scheme. The presented architecture effectively captures the process of diagnosing glioma. It is also important for data segmentation and augmentation in improving model performance. Talo et al. (2019) [16] used a Convolutional Neural Network model that produced a high accuracy rate of 95.23% to categorize brain tumors utilizing a dataset of 1074 MRI images.

Arif et al. (2019) [17], utilizing three BraTS datasets, each of which included four three-dimensional MRI scans of a single patient's brain tumors were divided into two categories. Both quantitative and qualitative methodologies were used in this investigation. All four of the patient's MRI sequences will be treated In their raw form because they collectively offer a complete perspective on the tumor. Secondly, for every MRI sequence, a 3D CNN model is trained to evaluate its performance and reach a peak test accuracy of 98.90%. To perform automatic brain tumor segmentation Karayegen and Aksahin et al. (2021) [18] present a semantic segmentation approach utilizing CNN on a three-dimensional dataset for brain tumor segmentation (BraTS), this consists of pictures produced using four different imaging methods. This approach was successfully implemented, with images in sagittal, and coronal, all of which enabled the accurate identification of the tumor's area and dimensions. An average prediction accuracy of 91.71% was achieved.

This author Guan et al. (2021) [19] initially improved the clarity by processing input images through contrast enhancement with nonlinear aspect processing techniques. Next, tumor locations were identified through segmentation and clustering techniques. This area was subsequently used along with the matching input picture to feed into EfficientNet to extract features. Although the accuracy of 98.04% was achieved using the MRI dataset fivefold cross-validation, this study is affected by high computational expenses as a result of having to train several networks. Mahmud et al. (2023) [20] Initiated A CNN classification model for brain tumors and an important dataset comprising 3264 Magnetic Resource Imaging datasets. After training, the CNN model identifies unique factors and categorizes the source photos into various tumor types. The accuracy of classifying brain tumors in this study was 93.30%. The outcomes underscore CNN algorithms' capacity to use MRI datasets to reliably identify brain cancers. Khan et al. (2020) [21] suggested a way to categorize different tumor kinds. The CNN approach integrates data enhancement as well as picture processing techniques to categorize the brain Magnetic Resource Imaging (MRI) visualizations as either non-cancerous or malignant. The validation data for the model evaluation, model parameter optimization, and data testing are created using the training data.. A performance transfer learning technique is used to compare the suggested CNN model using ResNet-50 and VGG-16 pre-trained models. The suggested model's accuracy scores are very good VGG-16 achieved 96% accuracy, while ResNet-50 achieved 89% accuracy.

Febrianto et al. (2020) [22] this study developed a method for tumor classification in MRI images the performance of two CNN prototypes to determine the most effective. The dataset used as input consists of MRI pictures organized and split into two distinct groups' malignancies and non-tumor pictures. Applying the utilizing function enhances the accuracy of CNN-based segmentation. During the image preprocessing step, the input pictures are wrapped and cropped to resize them to a uniform shape of (240, 240, 3) where 240 is the image width and height, and 3 represents the number of color channels as a result of the dataset's source photos' different sizes. The suggested framework produced a 93% accuracy rate, surpassing the first CNN model. Enhancing the quantity of convolutional layers enhanced the accuracy of the results. Irmak et al. (2021) [23] This Paper evaluated the performance of CNN architectures including Alex-Net, Res-Net, and VGG for the classification of meningioma, pituitary tumors, and gliomas. The researcher conducted the investigation using two distinct datasets to assess the effectiveness. Using CNN models that have already been trained, the labeling accuracy of Grades I to IV cancers was evaluated. Alex-Net delivered the maximum precision of the classification 92.66%. Karayegen and Aksahin (2020) [24] utilized a CNN algorithm that uses a collection of 257 MRI pictures to classify brain cancers. The model was developed to recognize unique photos and provide precise predictions. The study's categorization accuracy was 95.70%. Despite the dataset's tiny size. These findings highlight CNN models' ability to recognize brain tumors with accuracy and to identify important patterns and traits.

Özyurt et al. (2019) [25], this study introduced Neutrosophy-CNN (NS-CNN), A hybrid approach to brain tumor classification. The method comprised segmenting the images, extracting features categorizing the pictures with SVM and KNN classifiers and a CNN classifier. 160 brain MRI pictures were used in the study, 80 of which showed benign tumors and 80 of which showed malignant ones improved CNN features and the performance of SVM classifiers, yielding a validation data accuracy percentage of 95.62%. In contrast to the dataset utilization, (Huang et al. 2022) [26] used the BRATS-17 dataset, which had the largest total number of images 10,517 among all the research cited to train the AFM-Net model. They only achieved 92.10% accuracy in classification using the large dataset [27-28]. This accuracy is significantly less than the accuracy found in our most recent trial demonstrating the efficacy of our method for classifying brain tumors in Table 1.

Table 1. Literature Review

Author and Year	Data set used	Description	Classifier	Result
Arif et al. (2019)	BraTS datasets	TD-CNN-LSTM network outperforms 3D CNN	3D CNN	98.90%
Talo et al. (2019)	Dataset of 1074 MRI	Brain Tumor classification	CNN	95.23%
Karayegen et al. (2021)	BraTS datasets	3D brain tumor segmentation	CNN	91.71%
Guan et al. (2021)	MRI dataset	Improved the clarity of input images	Efficient-Net	98.04%
Mahmud et al. (2023)	3264 (MRI) dataset	Accurately diagnosing brain tumors	CNN	93.30%.
Khan et al. (2020)	Kaggle.com	Transfer learning technique	VGG-16, ResNet50	96% 89%
Febrianto et al. (2020)	Kaggle.com	5 LAYERS	CNN model	93%
Irmak et al. (2021)	Rider Rembrandt TCGA-LGG	13- Layered model with 2 CNN layers	CNN	92.66%
Karayegen and Aksahin (2020)	257 MRI images.	Brain tumor classification	CNN	95.70%
Özyurt et al. (2019)	160 brain MRI images	Classification using SVM and KNN classifiers	CNN	95.62%

Huang et al. (2022)	BRATS-17 SHCMU	Accuracy is considerably lower than the accuracy attained	AFM-Net	98.10%

3. Methodology

Image segmentation, extraction of features, classification, and preprocessing are the four main phases of the proposed categorization and detection scheme for brain tumors, which is displayed in Fig. 7. Below are specifics for each step. We used photos of brain tumors that were taken from several sources. To improve the clarity of the brain tumor images, we used an advanced hybrid contrast enhancement technique in the first stage. This technique combines the kurtosis function with the absolute mean deviation. Ultimately, the improved ELM model was able to categorize brain tumors into four different types' glioma, meningioma, pituitary, and no tumors.

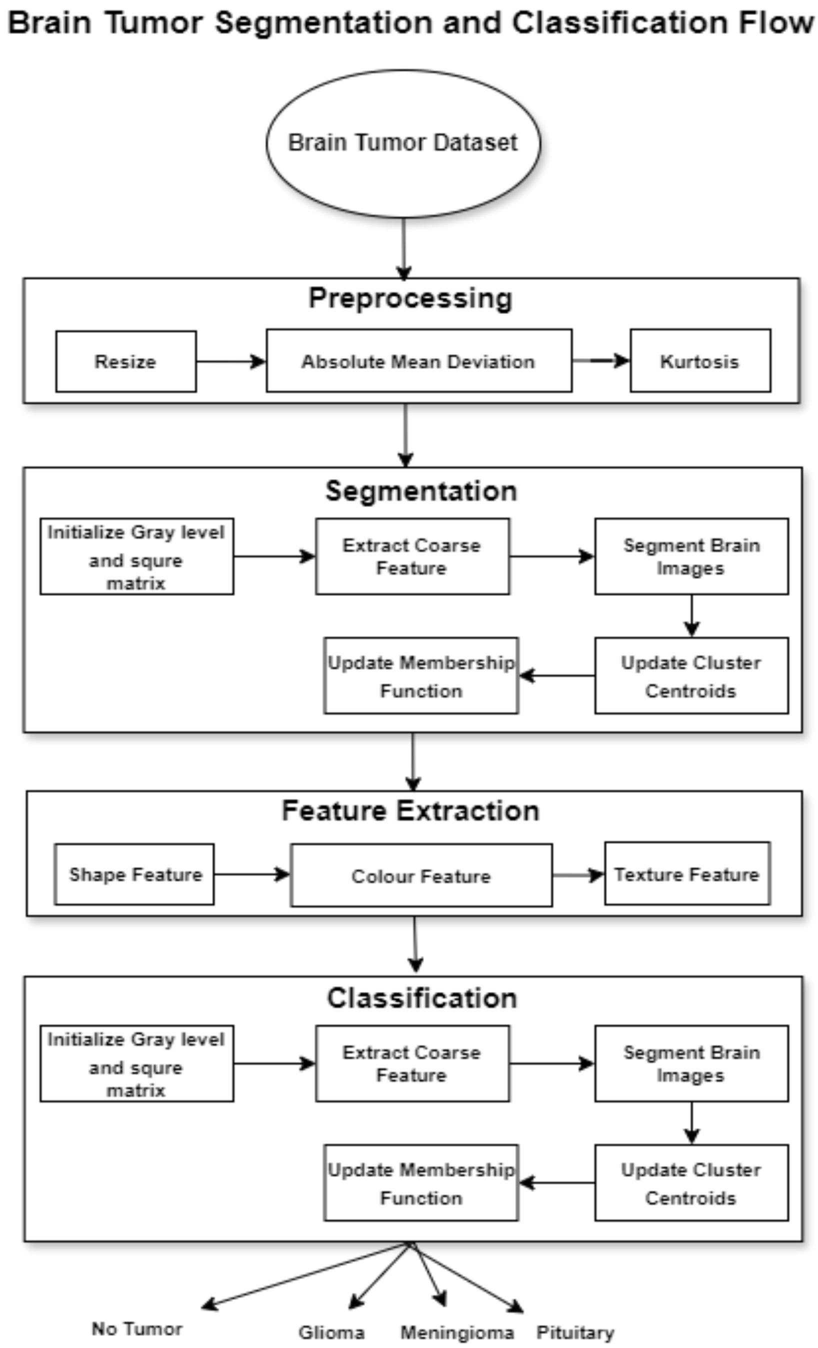

Figure 7. Brain Tumors Segmentation and Classification Flow Diagram

Typically the largest part, making up between 70 and 80 percent of the entire dataset. Depending on the dataset, this subset, which is used to train machine learning models, can contain thousands of photos. Usually makes up 10% to 20% of the dataset; it is used to evaluate training results and adjust model parameters. Typically, this subset consists of a few hundred to a few thousand photos. To ensure thorough model training and evaluation, both training and validation sets frequently contain a variety of image modalities (such as T1, T2, and FLAIR MRI), with the distribution within these modalities typically balanced presented in Fig.8. All BraTS multimodal scans are provided as NIfTI files (.nii.gz) present in Fig.9, a popular medical imaging format that is used to record different MRI settings and save brain imaging data from MRI scans.

1. T1: T1-weighted native pictures with a thickness ranging from 1 to 6 mm, obtained in axial or sagittal 2D slices.
2. T1c: Gadolinium-enhanced T1-weighted images, usually obtained in three dimensions with an isotropic voxel size of one millimeter for the majority of patients.
3. T2: T2-weighted images with a slice thickness of 2 to 6 mm that, were acquired using axial 2D acquisition.
4. FLAIR: T2-weighted FLAIR pictures with a thickness of 2 to 6 mm that are obtained in axial, coronal, or sagittal 2D slices.

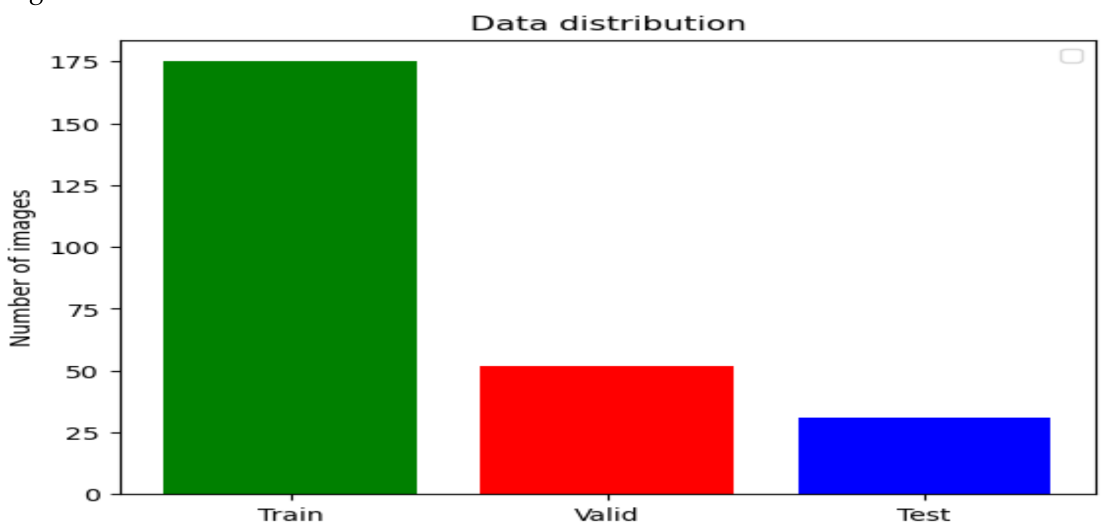

Figure 8. Training, Validation, and Testing of the number of images

One to four raters manually divided each image dataset according to a standard annotation process; the annotations were then examined and approved by neuroradiologists with experience. After being pre-processed, the data are dispersed.

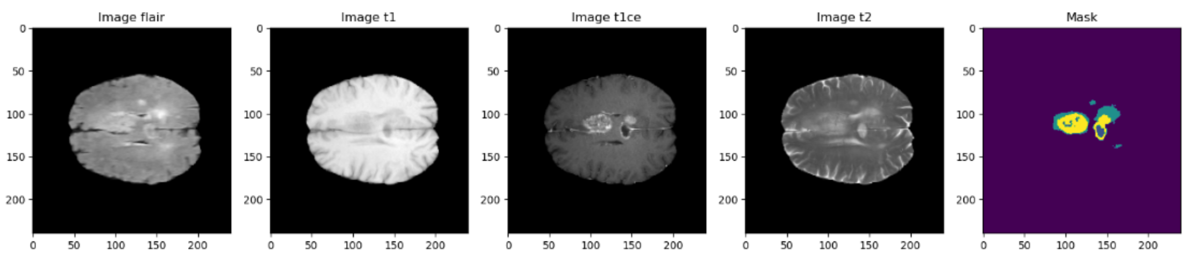

Figure 9. Show whole NIfTI data -> print each slice from 3d data.

In an axial slice, a brain tumor may appear as a mass disrupting the normal brain structure, often visible as a bright or dark area depending on the imaging type. This view reveals how the tumor affects the surrounding tissues and may show associated edema as a bright halo around the tumor. The coronal slice presents the brain from a front-to-back perspective, highlighting the tumor's extension across these planes and its impact on structures such as the ventricles. This view helps in assessing how the tumor displaces or distorts adjacent brain regions. Lastly, the sagittal slice provides a side view of the brain, showing the tumor's vertical spread and its effect on crucial structures like the corpus callosum or the brainstem, which aids in evaluating the tumor's influence on different brains.

In medical imaging, various techniques can reveal different aspects of a brain tumor, each offering unique insights into its characteristics. Magnetic Resonance Imaging (MRI**)** with T1-weighted sequences provides a detailed view of brain anatomy, where tumors might appear as areas of altered contrast, often standing out as darker or lighter spots against the normal tissue. When enhanced with gadolinium, contrast-enhanced MRI highlights tumors more vividly, showing them as bright spots due to the increased contrast agent accumulation in the abnormal tissue. On the other hand, T2-weighted MRI emphasizes fluid and edema, making tumors and their surrounding edema appear brighter, which helps in distinguishing them the tumor from adjacent structures. Diffusion-weighted imaging (DWI) further adds to the assessment by highlighting areas of restricted water diffusion, often indicating high tumor cellularity or the presence of aggressive tumors Fig.10**.**Functional MRI (fMRI)**,** while primarily used to assess brain function, can also help identify changes in brain activity related to the presence of a tumor.

By inheriting from the Sequence class, you can implement the __len__ and __getitem__ methods to define how many batches are generated and how each batch is fetched, respectively. Additionally, you can customize the data loading process to include specific logic for the training, validation, and testing phases.

For instance, during the training dataset, you might include data augmentation or shuffling, while for validation and testing, you may want to disable augmentation and ensure data is processed in a fixed order.

4. Results

The objective is to separate the various forms of brain tumors, such as non-enhancing tumors, enhancing tumors, and peritumoral edema. It calculates the overlap between the segmentation from the ground truth and the prediction; larger values correspond to better performance. DSC scores typically range from 0.60 to 0.80 based on the model and tumor subtype. Recent findings show in Fig.10. That sophisticated techniques, such as deep learning models (e.g., U-Net, Transformer-based architectures), can produce notable gains, frequently leading to high DSC scores and enhanced segmentation accuracy. Research teams can submit their algorithms to leaderboards on the BRATS dataset and compare the outcomes. This makes it easier to monitor development and pinpoint the best approaches.

Utilizing MRI slices from the BRATS dataset, divide brain tumors into three regions: enhancing tumor, peritumoral edema, and non-enhancing tumor.Tumor areas are highlighted by segmenting each MRI slice. Several tumor kinds are indicated by color-coded overlays or masks that are frequently included in the segmentation findings. Often depicted in a single hue, highlighting regions of aggressive tumor growth with contrast enhancement. Patients' tumors can differ greatly from one another, which can impact the segmentation outcomes show in Fig.11.

Instead of retraining the model, I will utilize this pre-trained model, which achieved 81% accuracy on mean IoU and 65.5% on Dice loss. Additionally, the accuracy findings to demonstrate how successfully the recommended fusion and selection approach found each feature extraction method, calculations are shown in Fig. 12.

To confirm the effectiveness of the suggested segmentation algorithm, it is benchmarked against several widely used existing techniques. Here is a graphical comparison of the two datasets categorization accuracy in Fig.13.

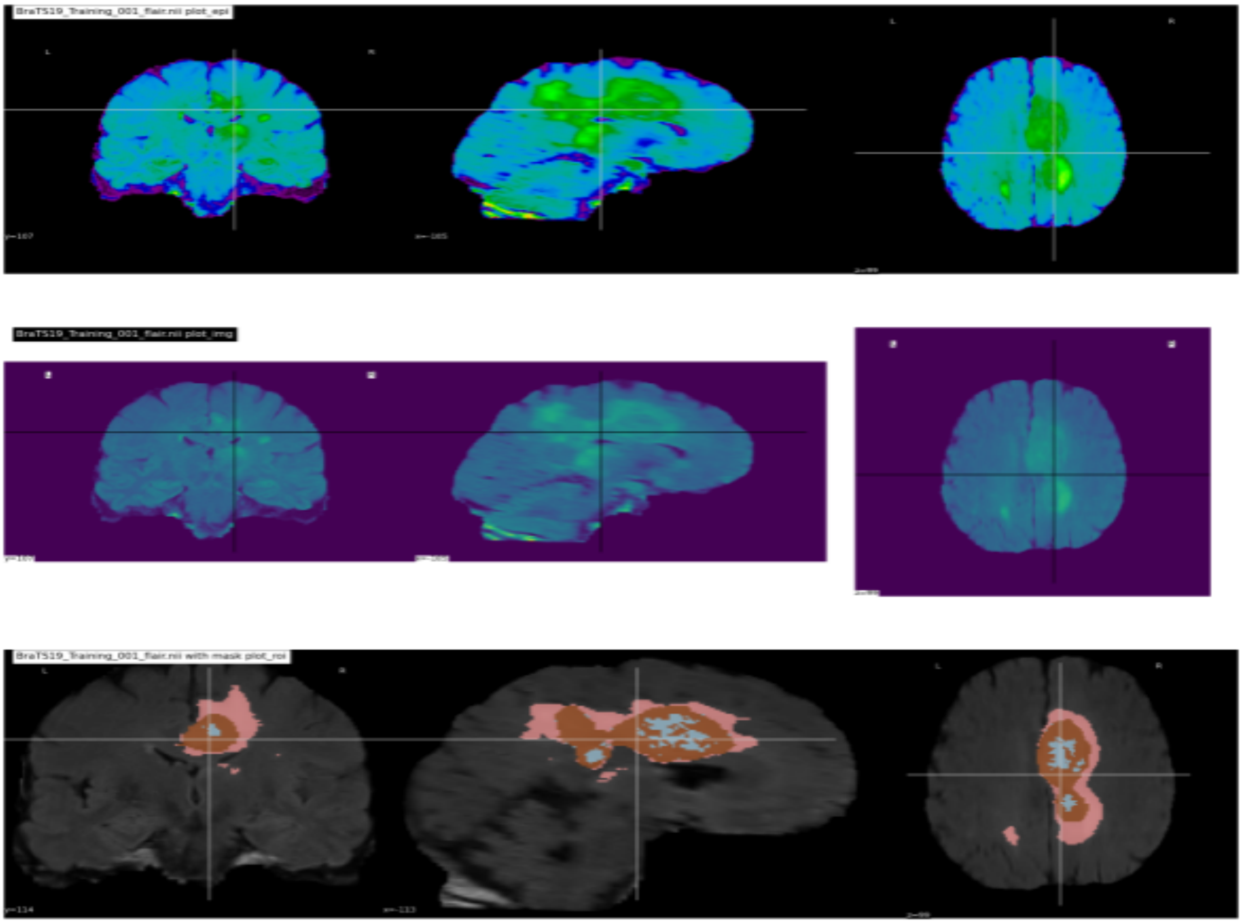

Figure 10. BrTas Dataset Image Segmentation Results

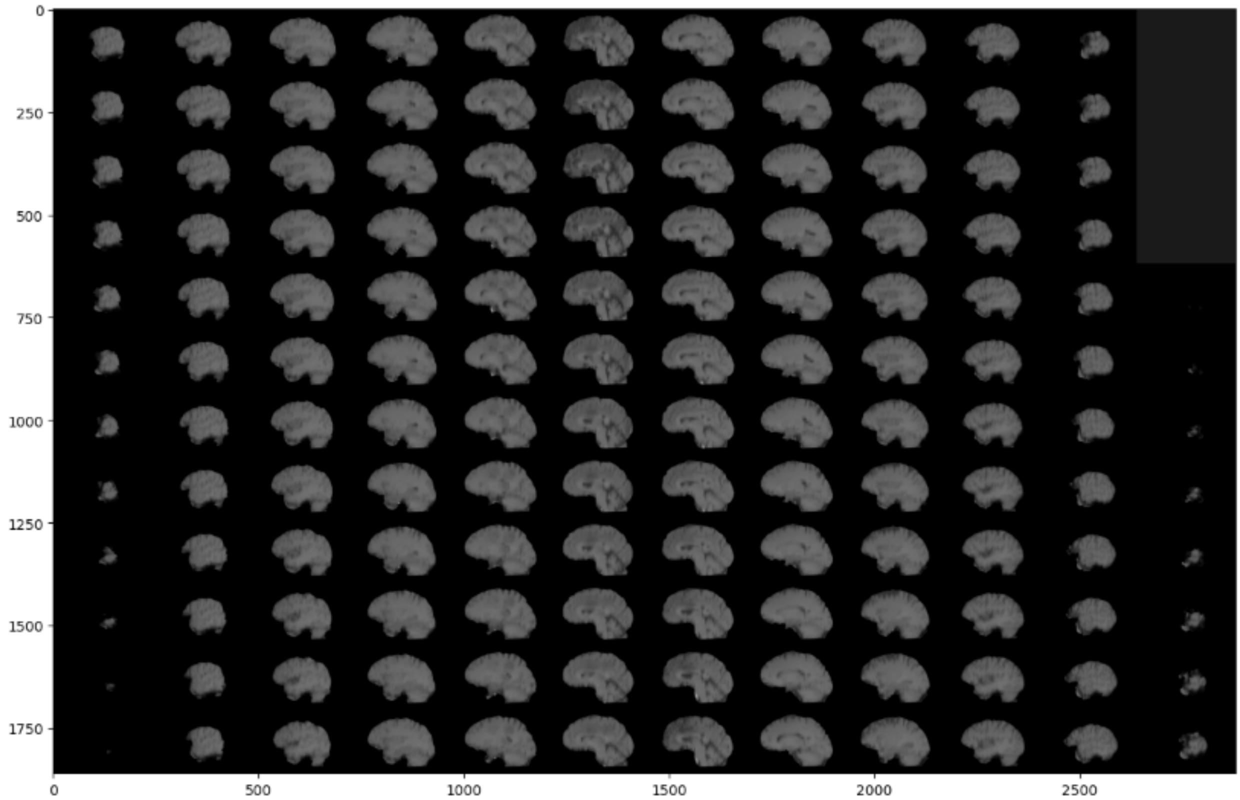

Figure 11. Show the segment of tumor for each above slice

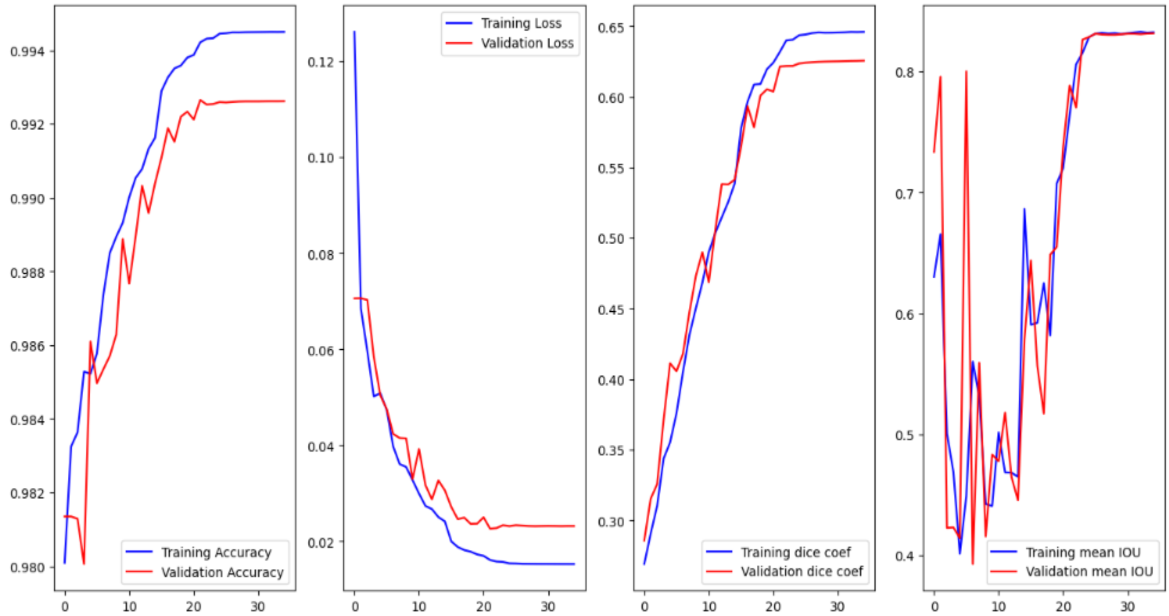

Figure 12. Taring Accuracy and Validation Accuracy results

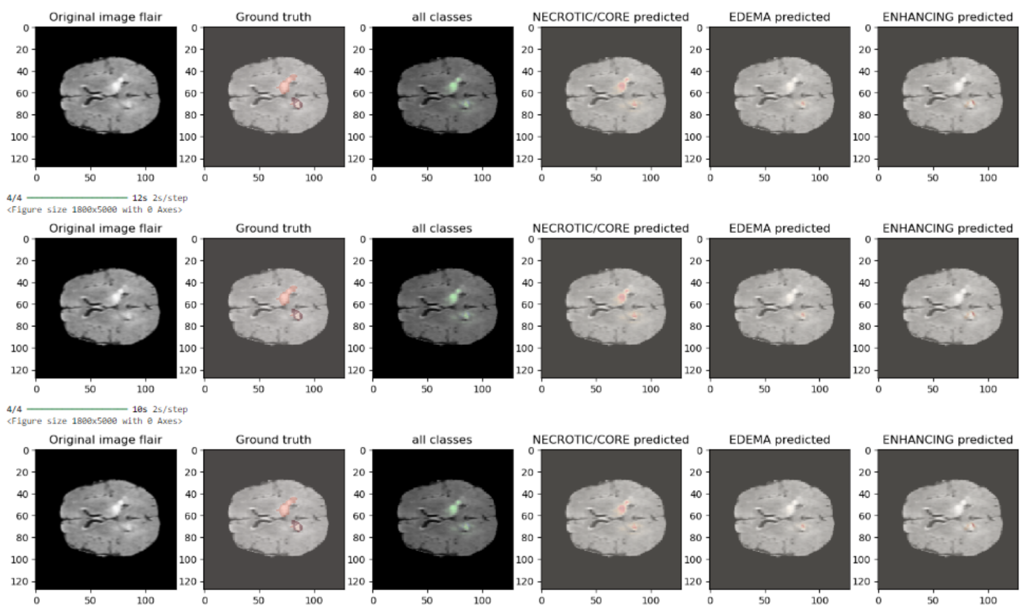

Figure 13. Brain Tumors Medical image results

5. Conclusion

This research suggests a unique technique for detecting as well as categorizing brain tumors through an enhanced U-net algorithm combined with ensemble learning techniques.. The proposed algorithm addresses uncertainty issues in MRI image segmentation and reduces computational complexity, thereby improving the accuracy of lesion detail identification. This model enhances brain tumor diagnosis by achieving faster and more accurate detection through the extraction of color, shape, and texture features. We want to implement the suggested approach and assess its efficacy with extensive MRI datasets. Other issues with the suggested system will be resolved in later research. These include problems with over-segmentation, difficulties in classification on large datasets, and challenges in selecting the most relevant features. Over-segmentation often results in inaccurate tumor identification at border regions, whereas the presence of irrelevant features can negatively impact classification accuracy. In the imaging of brain tumors, several types of MRI sequences are commonly used. T1-weighted (T1) pictures can be obtained in axial or sagittal two-dimensional slices, with slice thicknesses varying from 1 to 6 mm, providing detailed anatomical information. T1-weighted contrast-enhanced (T1c) images use Gadolinium to enhance contrast, typically obtained in 3D with an isotropic voxel size of 1 mm, which helps in better visualization of tumors. Fluid and edema are highlighted in T2-weighted (T2) pictures, which are obtained in axial 2D slices with a thickness of 2 to 6 mm. Based on the aforementioned conversation, it is clear that precise tumor segmentation is essential for achieving optimal accuracy in tumor diagnosis and analysis. Additionally, the combination of geometric and textural elements provided better outcomes than utilizing individual features alone when paired with an ideal feature selection method.

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