

# Hybrid Deep Learning Models for Brain Tumor Detection and Severity Assessment

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## Abstract

Brain tumor detection is crucial in medical imaging, significantly impacting treatment planning and patient outcomes. Traditional methods often struggle with the complex and heterogeneous nature of brain tumors. This paper introduces a novel hybrid deep learning approach, combining U-Net, ResNet-101, Generative Adversarial Networks, and Vision Transformers to enhance diagnostic accuracy, model generalization, improve the detection and severity classification of brain tumors. By integrating these state-of-the-art models, the system aims to provide precise tumor segmentation, robust feature extraction, enhanced generalization through data augmentation, and a comprehensive severity assessment, addressing key challenges in brain tumor imaging. U-Net is employed for precise tumor segmentation, while ResNet-101 provides deep feature extraction. GANs augment the dataset, improving robustness and generalization, and ViT captures long-range dependencies in images. These models are integrated using an ensemble learning approach, optimized through a genetic algorithm to assign optimal weights to each model's predictions. The ensemble model effectively captures both global and local features, significantly improving classification accuracy, precision, recall, and score compared to individual models.

**Keywords:** Brain Tumor, U-Net, ResNet-101, Generative Adversarial Networks

## 1. INTRODUCTION

Brain tumor is regarded as one of the deadliest and also considered as one of the common form of cancers both in young and adults according to statistics[1]. Brain tumor classification into sub type is a challenging problem because brain tumors vary heavily in shapes and sizes[2]. Moreover, different types of brain tumors may possess similar appearances thus making classification task more complex[3]. Among the sub types of brain tumors, three such as Meningioma, Pituitary and Glioma are most prominent which can roughly be compared with three stages of cancer[4]. So an early and efficient detection and classification of brain tumors is very important and can save lives to a great extent. That's why Medical image analysis is heavily focused on developing better classification techniques for classifying brain tumors. Cheng et al.[2] proposed an approach which relied upon manually delineated tumor borders to extract feature from the region of interests of T-1 MRI images where the best performance was achieved by an SVM model on bag of words (BOW) features and this is also regarded as one of the first works on figshare brain MRI image dataset[5]. Ismail and Abdel-Qadar[6] proposed to use Gabor filter and discrete wavelet

transform for feature extraction and then multi-layer perceptron for classification. The limitation of these approaches is that both of them use somewhat manual techniques for feature extraction. It is where CNNs hold clear advantage as they do not require manually segmented regions and can extract necessary features alone. That's why researchers are employing Convolutional Neural Network (CNN) based deep learning models for getting highly efficient brain tumor classification system. But problem with CNN is that it requires comparatively large amount of data for training. Due to the complexity of brain tumors, for classifying them from the MRI images, comparatively deep convolutional neural network is required but usually brain MRI image datasets are not that large. These two opposing conditions create a dilemma. For solving this dilemma, transfer learning [7] comes as a great option. Through transfer learning, one can use a deep pre-trained CNN model which was developed actually for another related application [5]. Adopting the concept of transfer learning, Khan Swati et al. [8] used pre-trained VGG-19 model for classifying brain tumors from figshare brain MRI image dataset. S. Deepak et al. [5] applied modified GoogLeNet model on the same figshare dataset using the same concept of transfer learning. Brain tumors are abnormal cell growths in the rigid skull that encloses the brain [9,10].

Any growth in a small space might cause problems. Any skull tumor may cause brain damage, posing a significant danger to the brain [11,12]. Brain tumors are the tenth leading cause of mortality in both adults and children [13]. Various tumor kinds have poor survival rates dependent on texture, location, and shape [14,15]. Brain tumors affect 700,000 people, with 80% benign and 20% malignant [16]. According to 2021 American Cancer Society projections, 78,980 persons were diagnosed with brain tumors, including 55,150 noncancerous and 24,530 malignant tumors (13,840 men and 10,690 females) [17]. Research indicates that brain tumors are the primary cause of cancer mortality in both children and adults globally [18]. Many disorders need digital medical images for diagnosis, which are also useful for training and research. The need for digitized medical images is rising. In 2002, the University Hospital of Geneva Radiology Department produced 12,000–15,000 pictures daily [19]. Medical reports and image studies need a reliable computer-aided diagnostic system. Manual medical ageing assessment is time-consuming, inaccurate, and errorprone [20]. Machine and deep learning are essential for medical diagnosis and treatment. Multiple algorithms for brain tumor identification and classification have shown strong performance and low error [21]. DL provides brain tumor classification using pre-trained CNN models for medical pictures such as GoogLeNet, AlexNet, and ResNet-34 [20,21]. DL employs multi-layered deep neural networks.

### 1.1 Challenges of brain tumor disease detection with AI

The efficient integration of Artificial Intelligence (AI) into healthcare necessitates both transparency and efficacy, despite its immense potential. The utilization of primary MRI data in conjunction with Machine Learning (ML) and Deep Learning (DL) algorithms to detect brain tumors poses several challenges. Here are important considerations for brain tumor detection and classification associated with our whole research procedure.

**Complexity of Diverse Data:** Multi-modal MRI datasets contain DWI, FLAIR, T1, T2, and T1 Fat-Sat images for brain information. Integrating these data types is complicated and requires study.

**Data Preprocessing and Feature Extraction:** In the case of preprocessing of primary MRI data, we face obstacles, including the need to standardize imaging protocols, mitigate artifacts, and reduce inter-subject variability. Feature extraction itself is challenging, requiring cautious selection to capture meaningful tumor

### 1.2 Characteristics

**Limited Availability of Annotated MRI data:** Annotating primary MRI scans is a laborious and time-intensive technique. The lack of well-annotated data for training models may limit the development of robust algorithms for MRI datasets.

**Class Imbalance and Tumor Rarity:** The rarity of brain tumors in comparison to normal brain tissue within MRI datasets leads to class imbalance. This imbalance might result in biased models struggling to effectively detect the minority class (tumors), impacting overall performance.

**Ethical and Legal Considerations in MRI Studies:** The implementation of AI-based medical diagnostic systems employing MRI scans poses ethical and legal problems, including difficulties relating to patient privacy, permission, and potential biases in the algorithms. These concerns demand cautious attention and resolution.

## 2. 2D U-Net

The 2D U-Net architecture of CNN has been employed for brain tumor segmentation[22]. Each dataset (BraTS 2017, 2018, 2019, and 2020) has used some preprocess technique. A data generator class has been used in this experiment to fit the dataset into the main memory. After that, the dataset was divided into train, test, and validation datasets and fed into the U-Net model. (BRAST 2017, 2018, 2019, 2020) has been compared in this experiment[22]. The 2D U-Net outperformed on BRAST dataset compared to other CNN- based models such as FCNN and RCNN. This model gives the most robust result on BRAST 2019 dataset compared to the other BRAST datasets. Since the difference between the BRAST datasets is almost negligible, thus this model can be used on any BRAST dataset. The U-Net model achieved highest Accuracy (0.9981), Mean IoU (0.9130), Precision (0.9974), Sensitivity (0.9971), Specificity (0.9991), Dice

Score (0.8409) and minimal Loss (0.0054) on BRAST 2019. The highest Dice Scores of Edema, and Enhancing 0.9545, and 0.9490, respectively, achieved on the BraTS 2017 dataset. The highest Dice Scores of 0.8846 for Necrotic achieved on the BraTS 2020 dataset. The difference between the obtained result on these datasets are very less. It shows that the difference between those BRAST datasets is insignificant.

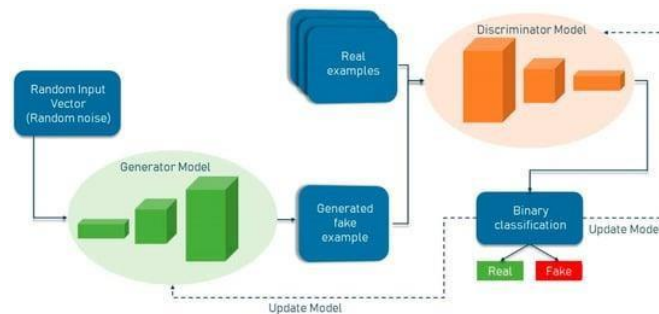
## 3. ResNet – 101

An automatic tool for classification of brain tumor from MRI data is presented where the image slice samples are passed into a Squeeze and Excitation ResNet model [23] based on Convolutional Neural Network (CNN). The use of zero-centering and normalization of intensity for smooth variation of the intensity over the tissues was also investigated as a preprocessing step which together with data augmentation proved to be very effective. A relative study had been done to prove the efficacy of the proposed CNN model in free tumor database. Experimental evaluation shows that the proposed CNN archives an overall accuracy rate of 89.93% without data augmentation. Addition of data augmentation has further improved the accuracies up to 98.67%, 91.81% and 91.03% for Glioma, Meningioma and Pituitary tumor respectively with an overall accuracy of 93.83%. Promising improvement with reference to sensitivity and specificity compared with some of the state- of-the-art methods was also observed.

## 4. Generative Adversarial Networks

In [24], an automatic end-to-end method based on Generative Adversarial Nets (GAN) is proposed for brain tumor segmentation. This method combines the generating model with the discriminant model and

takes GAN instead of conditional random fields (CRF) as high-order smoothing method. This method was validated in the BRATS 2015 database, it can be proven that this method achieves a competitive result and the use of GAN improve the performance of networks. Furthermore, comparing with other recent CNN-based methods, the approach only takes about 10.8s to segment a patient case.

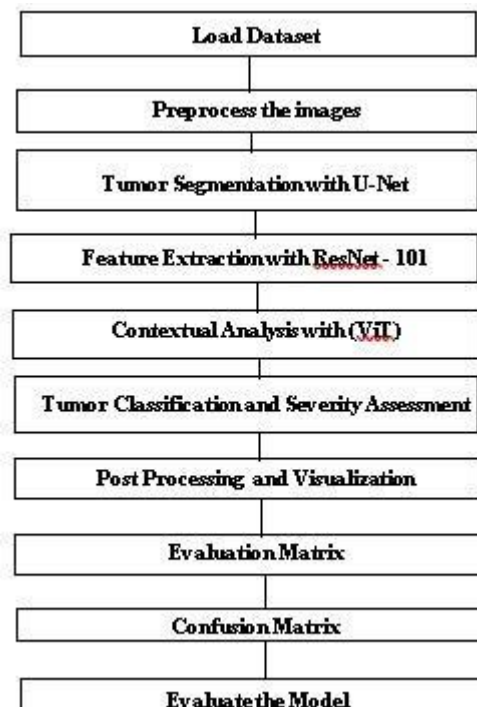


**Fig. 1 General Structure of GAN Network**

## 5. Proposed Methodology

### 5.1 Preprocessing

MRI scans are preprocessed to standardize dimensions, normalize pixel intensities, and remove noise. Data augmentation techniques, including rotations, translations, and flipping, are applied to increase dataset diversity. GANs are used to generate synthetic MRI scans to further augment the training data, ensuring the model can handle various tumor types and imaging conditions. The figure 2 shows the workflow of the proposed model.



**Fig 2. Workflow of Proposed Model**

### 5.2 Tumor Segmentation with U-Net:

The preprocessed MRI scan is passed through the U-Net architecture to segment the brain tumor from the surrounding tissue. U-Net's encoder-decoder structure identifies the tumor's location, providing a precise

segmentation mask that highlights the tumor boundaries. The output segmentation map is used to isolate the tumor region for further analysis.

### 5.3 Feature Extraction with ResNet-101:

The segmented tumor region is passed through ResNet-101 to extract high-level features from the image. The residual blocks of ResNet-101 capture deep patterns and textures that characterize different tumor types and their boundaries. These features are crucial for distinguishing between benign and malignant tumors and for classifying tumor severity.

### 5.4 Contextual Analysis with Vision Transformers (ViT):

The extracted features from ResNet-101 are input into the Vision Transformer model, which analyzes the global context of the image. ViTs process the entire MRI scan as a sequence of patches, learning relationships between different regions of the brain and enhancing the model's ability to detect and classify tumors, particularly those located in complex or subtle areas. ViTs improve the robustness of the model by considering the entire scan, providing a holistic view of the tumor's characteristics.

### 5.5 Tumor Classification and Severity Assessment:

The final feature representation, combining the outputs from U-Net, ResNet-101, and ViT, is passed to a fully connected layer for tumor classification. The model classifies the tumor as benign, malignant, low-grade, or high-grade based on the learned features. This classification is performed using a softmax classifier or similar mechanism to assess the severity of the tumor.

### 5.6 Post-Processing and Visualization:

The segmented tumor regions, along with the predicted severity classification, are visualized using overlays on the original MRI scan or heatmaps. This provides clinicians with a clear and interpretable output, aiding in diagnosis and treatment planning.

### 5.7 Evaluation Matrix:

The proposed model's performance is evaluated using various metrics, including accuracy, precision, recall, and F1-score. These measurements are calculated from the data provided in the confusion matrix, like True Positive, True Negative, False Positive, and False Negative, showing the model's progress. We have used the following equations for measuring the performance of our proposed model:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (1)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (2)$$

$$\text{F1 - Score} = 2 \times (\text{Precision} \times \text{Recall}) \quad (3)$$

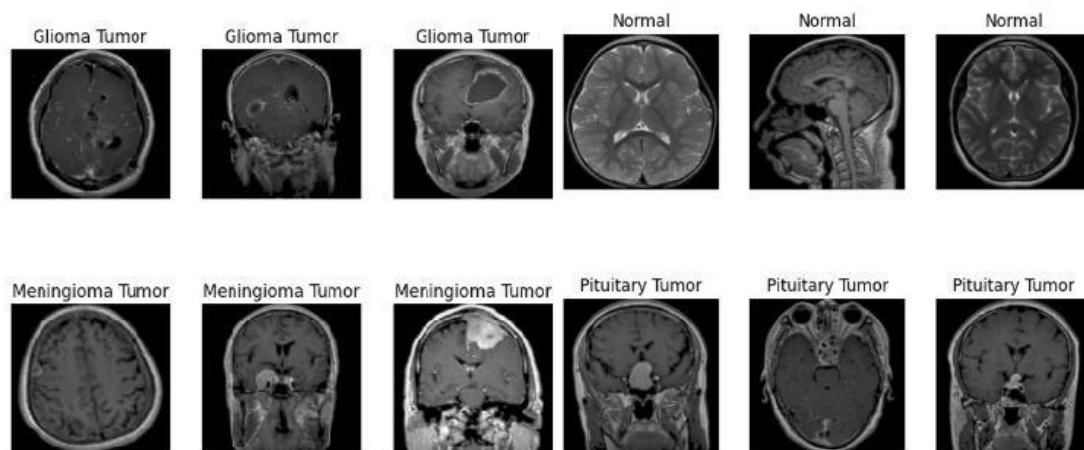
$$\text{Precision} + \text{Recall}$$

$$\text{Accuracy} = \frac{TP + TN}{\text{Total Number of Samples}} \quad (4)$$

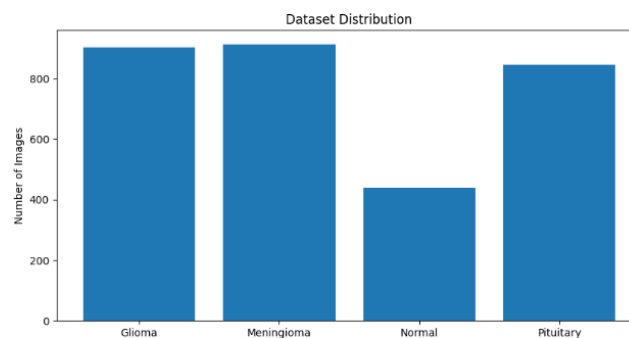
$$\text{Total Number of Samples}$$

Here TP represents True Positive and FP represents False Positive and TN represents True Negative.





**Fig 3. Glioma, Meningioma, Pituitary Tumor**



**Fig 4 Dataset Distribution**

## 5.7 Confusion Matrix

A confusion matrix is a tool used to visualize the performance of a model for brain tumor detection. It shows the correct and incorrect predictions made by the model, which can help identify areas for improvement and gain insights into the model's predictive behavior.

Here are some other metrics used to evaluate the effectiveness of brain tumor detection models: Accuracy, Precision, Recall, F1 score, and Validation loss.

True Value	Flair	99.6%	0.3%	0.0%	
	T1	0.0%	99.9%	0.0%	0.1%
	T1CE	0.2%	0.2%	99.6%	0.0%
	T2	0.0%	0.0%	0.1%	99.8%
		Predicted Value			

**Fig 5. Confusion Matrix**

Brain tumor detection models can be trained on MRI datasets with labeled tumor and non-tumor images. Some models use Convolutional Neural Networks (CNNs) to automate the analysis of MRI images. This can be more efficient and accurate than the traditional method of radiologists manually examining MRI

scans.

## 6. Conclusion

In this paper U-Net is employed for precise tumor segmentation, while ResNet-101 provides deep feature extraction. GANs augment the dataset, improving robustness and generalization, and ViT captures long-range dependencies in images. These models are integrated using an ensemble learning approach, optimized through a genetic algorithm to assign optimal weights to each model's predictions.

The ensemble model effectively captures both global and local features, significantly improving classification accuracy, precision, recall, and score compared to individual models. The proposed approach achieves a notable accuracy rate of 96%, demonstrating its potential to advance medical image analysis and improve patient outcomes in neuroimaging.

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