Adv. Eng. Tec. Appl. 13, No. 1, 23-31 (2024)

Advanced Engineering Technology and Application
*An International Journal*

http://dx.doi.org/10.18576/aeta/130103

# Integrated Deep Learning Approach for Brain Tumor Detection and Segmentation in MRI Images

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Received: 27 Jul. 2024, Revised: 2 Aug. 2024, Accepted: 5 Aug. 2024.

**Abstract:** This study examines the use of deep learning techniques for magnetic resonance imaging (MRI)-based brain tumor categorization in lower-grade gliomas by applying the manually segmented FLAIR abnormality masks that were acquired from The Cancer Imaging Archive (TCIA) and the LGG Segmentation Dataset, which include brain MR images. We propose a classifier model based on ResNet50, and a segmentation model named U-NET, leveraging knowledge from earlier research investigating the relationship between form data collected by deep learning algorithms and genetic subtypes of lower-grade gliomas. This model reaches a remarkable accuracy of 94.75% when trained to identify whether tumors are present or absent. F1-score, precision, and recall measures are included in the evaluation to give a thorough understanding of the model's functionality. These findings highlight the promise of sophisticated image processing methods for precise and automated brain tumor classification, with ramifications for improving neuro-oncology clinical processes and diagnostic accuracy.

**Keywords:** Deep learning; Classification; Segmentation; MRI brain tumor.

## 1 Introduction

With about 100 billion neurons, the human brain is a marvel of complexity and functionality in the human body.[1] But even with its extraordinary powers, it is not immune to illness; in industrialized nations, brain tumors are becoming a serious threat to adults and children alike.[2] Brain tumors are the tenth most common cause of death in these populations, according to reports, which highlights the critical need for better diagnostic and treatment methods.[3] The enormous impact of these brain tumors on public health is shown by the projection that the incidence of primary brain tumors alone will cause 18,280 deaths among adults in the USA in 2022. From harmless growths to violent, life-threatening tumors, brain tumors represent a wide range of malignant cells that originate in the intracranial tissues of the brain and vary significantly in terms of their malignancy[4].

Given their various cellular origins, molecular characteristics, and clinical symptoms, brain tumors are complicated diseases that require a multidisciplinary approach to comprehend fully. Because of their complex biology and microenvironment, brain cancers are challenging to classify, with each tumor subtype having distinct traits, prognostic implications, and responses to treatment. Historically, histopathological characteristics—such as cell morphology and genetic markers—have been used to distinguish between different types of brain tumors in the classification process. However, since the development of molecular profiling methods, the genetic landscape of brain tumors has become more apparent, exposing unique molecular subgroups that influence tumor biology and treatment approaches.

Among brain tumors' challenges, a precise and convenient conclusion remains foremost for directing persistent administration and treatment choices. Determination ordinarily includes imaging tests, neurological examinations, and tissue biopsies to characterize the tumor's area, estimate, and histological highlights. Attractive Reverberation Imaging (MRI) has developed as the foundation of neuroimaging in brain tumor determination, advertising prevalent delicate tissue differentiation and multiplanar imaging capabilities without the requirement for ionizing radiation.[5] Progressed MRI strategies, such as diffusion-weighted imaging (DWI), perfusion-weighted imaging (PWI), and attractive reverberation spectroscopy (MRS), give extra utilitarian and metabolic data that help in tumor characterization and treatment arranging. [6]

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Even with MRI's diagnostic value, it is still challenging to precisely identify tumor locations inside the intricate structure of the brain. Tumor segmentation is essential for determining tumor burden, treatment response, and disease progression by separating the tumor's boundaries from the surrounding normal tissue. Automated segmentation techniques are necessary since radiologists' manual segmentation is time-consuming and subject to interobserver variability.[7] Automating tumor segmentation tasks has shown fantastic potential in recent years thanks to deep learning techniques, a subset of artificial intelligence (AI) that replicates the human brain's neural networks. MRI scans of brain tumors have shown better performance when segmented by convolutional neural networks (CNNs), which use massive datasets to learn intricate spatial patterns and attributes linked to various tumor kinds.[8]

Brain tumor imaging has been transformed by incorporating deep learning algorithms into computer-aided diagnostic (CAD) systems. This makes it possible to segment tumors quickly and accurately on a previously impossible scale. CAD systems driven by deep learning can help radiologists identify, schedule, and track brain tumors and assist them in evaluating MRI images. AI-driven predictive models may support personalized medicine for brain tumors by forecasting therapeutic response, prognosis, and disease recurrence based on patient features and imaging biomarkers.[9]

This work classifies and differentiates brain tumors using the deep learning algorithms ResNet and U-Net. These sophisticated neural network designs automate the identification of different types of tumors and accurately delineate tumor boundaries in magnetic resonance imaging (MRI) data. The project aims to increase the accuracy and efficiency of brain tumor diagnosis by using U-Net for segmentation and ResNet for classification. This will improve patient care and the planning of neuro-oncology therapy.

## 2 Associated works

This study [10] demonstrates that early diagnosis of brain tumors increases treatment success and patient survival. The study uses MRI images to investigate supervised, unsupervised, and deep learning (DL) AI approaches for brain cancer diagnosis. Early detection is becoming more complex as technology advances faster than medical professionals can use it. This could cause a misconception of the diagnosis. The study highlights the necessity for ongoing research and efficient automated systems to diagnose brain tumors.

It investigates the relationship between therapeutic choices, clinical diagnosis, and biomedical imaging [11]. MRI is used to segment brain tumors. Brain cancer has been described via neuroimaging and statistical modeling. The paradigm has shifted due to deep learning, making sophisticated computer vision techniques possible for automated and more precise diagnosis. Deep understanding and statistical methods can be coupled with medical, artificial intelligence, and statistics. This article uses deep learning, statistics, and probabilistic brain imaging models to examine clinical oncology automation. There are criticisms of these models. The findings demonstrate the potential for automated clinical oncology systems, particularly for MRI brain tumor segmentation, using the combination of data-driven deep learning and model-driven classical statistics.

This work [12] emphasizes the significance of precisely defining tumor regions to overcome the significant difficulty of brain tumor segmentation in medical image analysis. Deep learning has recently advanced and shown promise in several computer vision applications, leading to the use of deep learning in brain tumor segmentation. For this goal, the survey thoroughly analyzes more than 150 scientific articles using deep learning techniques, including topics like multi-modality processes, network architecture design, and segmentation under imbalanced settings. The paper discusses potential paths for progress in this crucial field of medical imaging research and offers insights into the technological breakthroughs and accomplishments in deep learning-based brain tumor segmentation.

This study [13] assesses different image segmentation algorithms for identifying brain tumors using MRI scans to determine the best approach. Using the Brain Tumor Image Segmentation Benchmark (BRATS) dataset-2018, methods including Otsu's, watershed, level set, K-means, HAAR Discrete Wavelet Transform (DWT), and Convolutional Neural Network (CNN) are compared. With a calculated accuracy of 91.39% and a response time of 2.519 seconds in MATLAB simulation, CNN is the most accurate method. In addition to highlighting CNN's advantages over competing techniques, the study suggests its applicability to machine learning models and embedded hardware solutions for brain tumor diagnostics. Researchers and industries looking for the best deep learning-based algorithms for brain tumor segmentation can learn a lot from this study.

The paper [14] tackles the problem of deep learning segmentation techniques' need to extract features from multimodal glioma pictures acquired by magnetic resonance imaging (MRI). To overcome this problem, the authors suggest an Automatic Weighted Dilated Convolutional Network (AD-Net), which uses a channel feature separation learning technique to learn multimodal brain tumor features using an auto-weight dilated convolutional unit (AD unit). The AD unit uses dual-scale convolutional feature maps to obtain channel separation features. These maps are fused in encoding layers by two learnable parameters automatically modified by gradient backpropagation. Additionally, the technique uses deep supervision training for quick fitting and the Jensen-Shannon divergence to constrain feature map distribution. With Dice scores of 0.90, 0.80, and 0.76 for the whole tumor (WT), tumor core (TC), and enhancing tumor (ET), respectively, experimental results on the BraTS20 dataset highlight the efficacy of the suggested method and highlight its potential for precise multimodal brain tumor segmentation.

The study [15] highlights how crucial early brain abnormality discovery is to lowering death rates and enabling efficient treatment planning. One unique non-invasive diagnostic technique that provides excellent soft tissue contrast and high-resolution images is magnetic resonance imaging (MRI). Automated tumor segmentation is necessary in medical imaging applications since manual segmentation of aberrant brain tissues takes a long time and requires professional efficiency. This in-depth analysis examines the latest advancements in brain tumor segmentation, including deep learning techniques, machine learning strategies, and traditional approaches. It highlights the superiority of deep learning in automatic segmentation and covers machine learning algorithms, statistical and atlas-based models, and deep learning techniques. The manuscript describes tissue segmentation and classification using convolutional neural network designs, datasets, and state-of-the-art deep learning techniques. It ends with suggestions for future work and unresolved issues in brain tumor segmentation, which will be very helpful to medical imaging researchers.

This work [16] sheds light on the difficulties in clinically monitoring brain disease metastases, especially when there are several metastases, making manual assessment more time-consuming. Accurate volumetric measurement of lesions and surrounding edema is critical for clinical decision-making, even if the Response measurement in Neuro-Oncology Brain Metastases (RANO-BM) guideline is frequently used to evaluate therapy response. Nevertheless, unlike larger gliomas, segmenting tiny brain metastases—which are usually smaller than 10 mm—presents challenges. The paper presents the BraTS-METS dataset and the challenge to improve clinical outcomes and prediction accuracy, which aims to advance automated brain metastasis identification and segmentation systems.

To monitor and diagnose patients' health, this study [17] uses deep learning algorithms on brain MRI scans, which are particularly sensitive in identifying a wide range of chronic nerve illnesses. Because convolutional neural networks (CNNs) are so good at processing visual information, they are frequently employed in medical image analysis. The paper presents a novel modular deep learning model to improve classification performance while addressing the drawbacks of current transfer learning techniques like DenseNet, VGG16, and simple CNN architectures. The model was trained using two alternative splitting techniques: an 80/20 training-testing split and 10-fold cross-validation, utilizing publicly available photos of brain tumors from the Kaggle database. The results demonstrated the model's potential, which showed better classification performance than transfer learning but more processing time.

This study [18] employs a 3D deep learning model to enhance classification accuracy by identifying brain cancers using MRI data. Numerous research studies in this field employ 2D models; however, they frequently perform poorly because of the drawbacks of 2D data. The 3ACL model, which combines attention, convolutional, and LSTM components in a single learning architecture, makes end-to-end learning and increased feature representation capacity possible. The model retains spatial information using 3D MRI scans without converting them to 2D data. The suggested method's effectiveness in classifying brain tumors was demonstrated by the BRATS 2015 and 2018 datasets, which had accuracy rates of 99.29% and 98.90%, respectively.

Brain tumors need to be accurately identified to identify the best course of therapy and prognosis [19]. MRI is the recommended diagnostic technique because of its superior imaging capabilities. However, manual brain tumor segmentation takes time; hence, automated techniques are required. With precise and efficient analysis, artificial intelligence (AI), machine learning (ML), and deep learning (DL) have transformed illness detection. This study suggests ResNet50, feature extraction, and augmentation to detect brain tumors. The proposed model increases accuracy using CNN datasets already trained for transfer learning. Compared to existing techniques, the model's performance evaluation criteria demonstrate its promise as a groundbreaking deep-learning brain cancer classification system.

## 3 Methodology

Our methodology consists of several crucial phases, such as preprocessing the data, creating a segmentation model, creating a classifier model, and merging the two models into a single pipeline for thorough tumor detection.

Data Preprocessing:

The dataset included brain MRI pictures and matching masks that showed the locations of tumors. It was obtained from the Kaggle database. Data preprocessing first required arranging the dataset according to image pathways and patient IDs. This stage ensured the data was sorted correctly and ready for further examination.

**Resnet Classifier Model:**

Skip connections were introduced by Residual Networks (ResNet) to address the vanishing/exploding gradient problem in deep neural networks. ResNet allows the network to easily fit residual mappings, allowing for intense training without gradient-related issues. Like ResNet-34, the architecture usually uses a 34-layer basic network architecture enhanced by shortcut connections. Impressive speed is the outcome. ResNet designs, such as Residual Blocks, are applied to image recognition tasks and are implemented with TensorFlow and Keras. ResNet revolutionized deep learning with skip connections, which are now essential for many tasks like image recognition and self-supervised learning. Based on a ResNet50 architecture, the classifier model was developed. The model was fine-tuned for tumor detection after being pre-trained on ImageNet. The essential stages were freezing the previously learned layers and adding new layers for classification. A categorical cross-entropy loss function was used to train the model, and the Adam optimizer was used to optimize it.

**Segmentation model:**

In ResUNet, we combine Resnet-inspired Residual Connections with the U-NET architecture. The fusion of both fast and deep networks is a strategic way to alleviate the problem of sluggish training and biomedical image segmentation. ResUNet enables a more significant contrast in gradients, which makes the training process smoother. Additionally, this helps in getting better results. This is accomplished through connections of shortcuts or skipped. ResUNet, implemented with frameworks like TensorFlow and PyTorch, is now widely used in medical imaging. The following reasons are stability and accuracy, which provide for tasks like precise segmentation. The ResUNet model was made significantly to determine the exact position of tumors in MRI images. The general segmentation model used to create proper tumor masks involved convolutional layers in different formats and up-sampling blocks. Tversky loss is dealt with as the model's loss function, which was optimized using the Adam optimizer, which the model trained with.

**Combined pipeline:**

The final stage was to combine the segmentation and the classifier model into a single model for end-to-end tumor detection. MRI image analysis will be done by this pipeline one by one, starting with the use of the classifier model, which checks any tumors in the images. The segmentation model will then determine if an image is needed and send it if necessary to enable precise tumor localization.

**Evaluation metrics:**

Several important metrics were used to assess the segmentation and classification algorithms to locate and identify brain tumors.

**Classification metrics:**

Accuracy is defined as the proportion of correctly identified samples to total samples. The predictive power of the model to identify tumorous brain MRI image regions is evaluated.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

where:

$TP$: True Positives

$TN$: True Negatives

$FP$: False Positives

$FN$: False Negatives

Confusion Matrix: Displaying the quantity of true positives, true negatives, false positives, and false negatives, the confusion matrix offers a thorough analysis of the model's predictions. Additional metrics, including recall, precision, and F1-score, can be obtained from the confusion matrix.

Precision: The percentage of true positive predictions among the model's positive predictions is measured by precision, sometimes called positive predictive value. It shows how well the model can prevent false positives.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

where: $TP$: True Positives, $FP$: False Positives

Recall (also called sensitivity): The proportion of correct optimistic predictions among all positive cases in the dataset is recalled by recall, which can also be defined as a sensitivity measure. The accuracy of how well the network can find input data is a good example.

F1-Score: Therefore, the harmonic mean of its precison and recal is evaluated as a balanced indicator of the model's performance. It is helpful for data with such imbalances because it considers errors of type 1, as well as errors of type 2.

$$F1\ score = 2 \times \frac{Precison \times Recall}{Precision + Recall} \tag{3}$$

**Segmentation metrics:**

Tversky Score: A similarity measure for the effectiveness of segmentation models. False positives and negatives measure the degree of geographic agreement between predicted and ground truth masks. Higher Tversky scores suggest greater segmentation accuracy.

$$T_{\alpha,\beta}(X,Y) = \frac{|X\cap Y|}{|X\cap Y| + \alpha|X-Y| + \beta|Y-X|} \tag{4}$$

where:

$X$ and $Y$ are the two sets being compared.

$\alpha$ and  are parameters that control the relative importance of the size differences between the two sets.

Dice Coefficient: The geographic overlap between the anticipated and ground truth masks is measured by the Dice coefficient, also called the Sørensen–Dice coefficient. Higher numbers indicate more significant overlap and better segmentation performance. The range of values is 0 to 1.

$$Dice\ Coefficient = \frac{2|X\cap Y|}{|X| + |Y|} \tag{5}$$

where:

X and Y are the two sets being compared.

|X∩Y| is the number of common elements in sets X and Y.

|X| and |Y| are the sizes of sets X and Y, respectively. Intersection over Union (IoU): divides the intersection area by the union area to determine how much overlap exists between the ground truth and expected masks. It offers a thorough assessment of segmentation accuracy, especially when dealing with objects with uneven shapes or unbalanced classes.

## 4 Results

**Classification results:**

The classifier model successfully distinguished between photos with and without tumors, as seen by its excellent accuracy of almost 95% on the test set. A thorough examination of the confusion matrix validated the model's performance, showing few misclassifications. As in Figure 1, a comparison between the training loss and validation loss was made, while Figure 2 shows the training accuracy and validation accuracy results; in Figure 3, a confusion matrix was visualized to show how well the model classified the tumors.

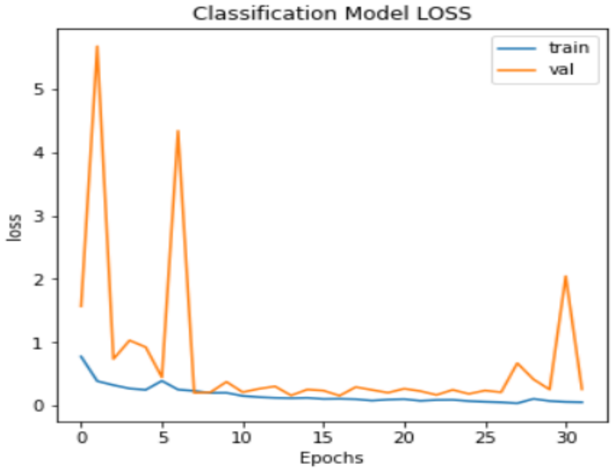


**Fig. 1:** training and validation loss results.

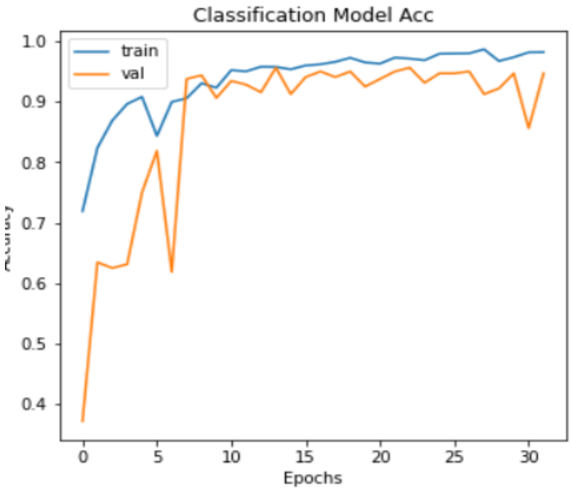


**Fig. 2:** training and validation accuracy results.

**Segmentation results:**

The segmentation model, created to locate tumors, performed well, achieving a Tversky score higher than 90% on the test set. This score represents the model's precision in locating tumor areas in the MRI pictures. The accurate delineation of tumor boundaries was validated by visual inspection of the segmentation data, demonstrating the model's effectiveness in tumor localization. As in Figure 5, a comparison between the training loss and validation loss was made, while Figure 6 shows the training accuracy and validation accuracy results.

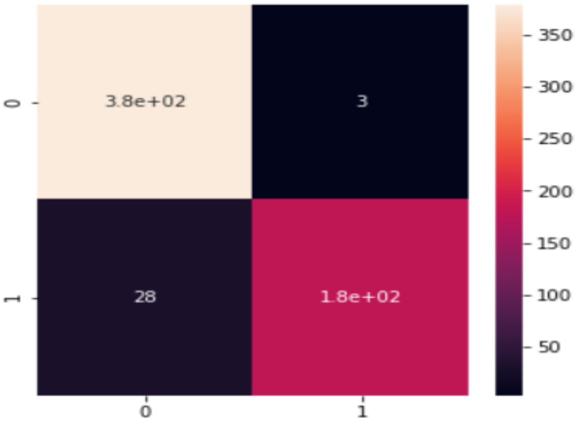
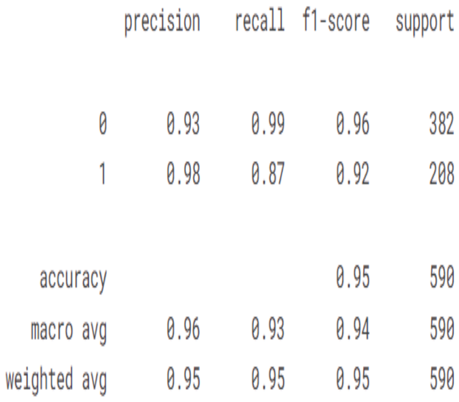


**Fig. 3:** Confusion matrix of the Resnet classifier.



```
              precision    recall  f1-score   support

           0       0.93      0.99      0.96       382
           1       0.98      0.87      0.92       208

    accuracy                           0.95       590
   macro avg       0.96      0.93      0.94       590
weighted avg       0.95      0.95      0.95       590
```

**Fig. 4:** Classification report.

**Fig. 5:** Training and validation of Tversky loss results.

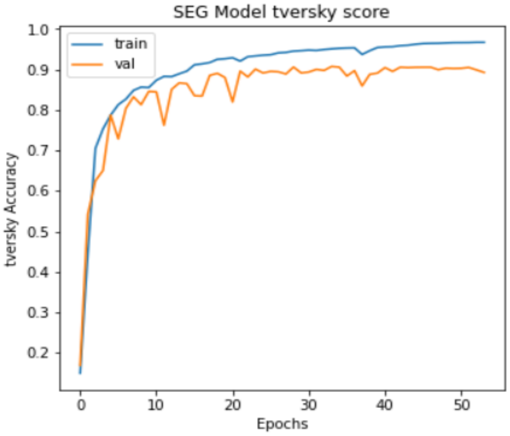


**Fig. 6:** Training and validation accuracy results.

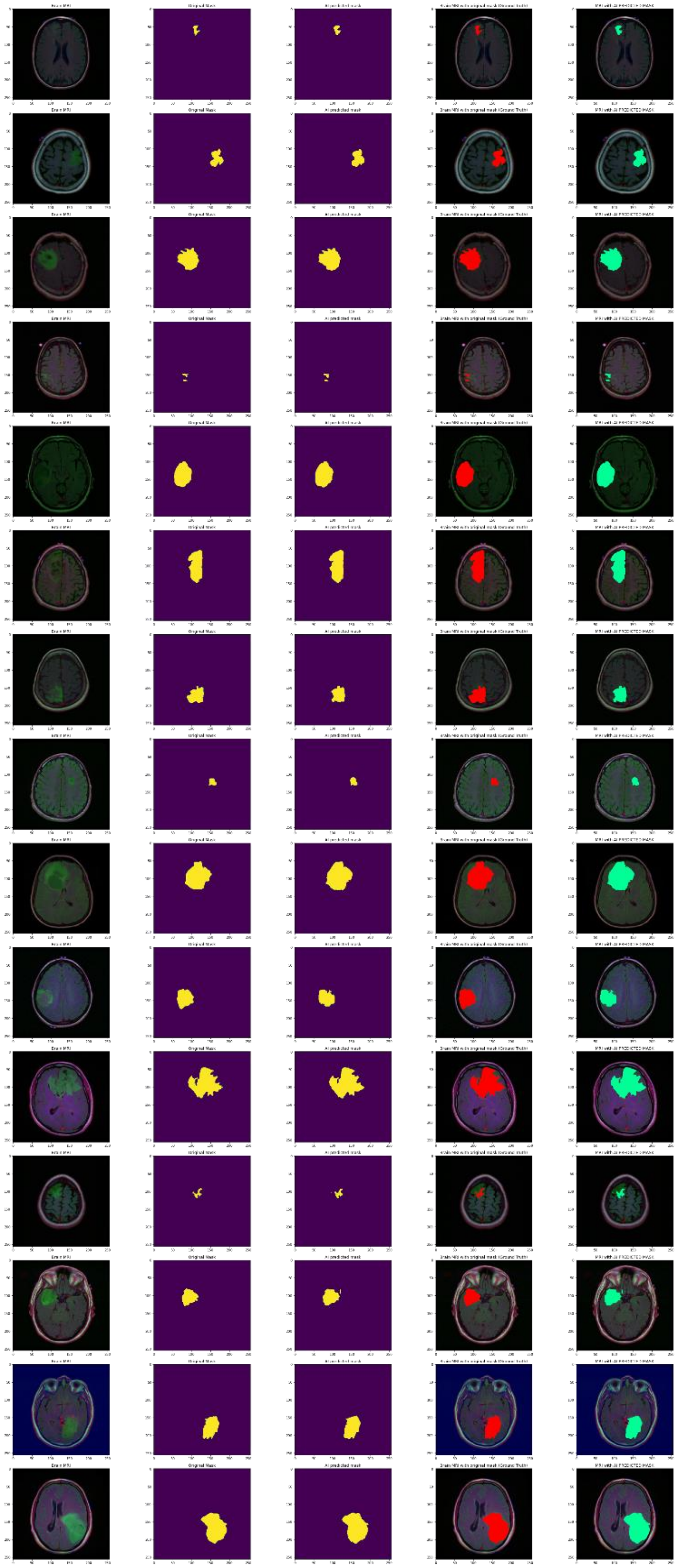


**Fig. 7:** The results of the combined pipeline.

## 5 Conclusions

The paper described creating and evaluating segmentation and classification models for deep learning-based brain tumor detection. While the segmentation model correctly delineated the boundaries of tumors within MRI images, the classification model showed excellent accuracy in differentiating between tumorous regions and those that weren't. The efficacy of the models was demonstrated by evaluation criteria like precision, recall, F1-score, Tversky score, Dice coefficient, and Intersection over Union. These technologies have a great deal of promise to support physicians in the early detection, accurate localization, and treatment planning of brain tumors, highlighting their essential role in enhancing patient outcomes and care in neuro-oncology—subsequent investigations endeavor to augment these models even more, guaranteeing their sustained applicability in medical contexts.

## Acknowledgment

We extend our heartfelt appreciation to the dedicated scientists and researchers whose contributions have been instrumental in developing this track. Their pioneering work and invaluable insights have laid the foundation for our research. We are grateful for their innovative ideas, groundbreaking discoveries, and tireless efforts in advancing the field. Their expertise and commitment to excellence have inspired and guided our endeavors, shaping this project's trajectory. We deeply admire and acknowledge their significant contributions, which have enriched our understanding and propelled the progress of this track.

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