# Reflect of 3D Brain Tumor Segmentation and Classification

**BY**

**Anika Islam**
**ID: 201-15-13930**

**FINAL YEAR DESIGN THESIS REPORT**

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**Supervised By**

**Abdus Sattar**
Assistant Professor
Department of CSE
Daffodil International University

**Co-Supervised By**

**Ms. Nasima Islam Bithi**
Lecturer
Department of CSE
Daffodil International University

**DAFFODIL INTERNATIONAL UNIVERSITY**

**DHAKA, BANGLADESH**

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## APPROVAL

This Project titled **"Reflect Of 3D Brain Tumor Segmentation and Classification"**, submitted by **Anika Islam**, ID No: **201-15-13930** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 15/07/2024.

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## DECLARATION

I hereby declare that, this project has been done by me under the supervision of**Abdus Sattar,Assistant Professor, Department of CSE,** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

**Supervised by:**

**Abdus Sattar**
Assistant Professor
Department of CSE
Daffodil International University

**Co-Supervised by:**

**Ms. Nasima Islam Bithi**
Lecturer
Department of CSE
Daffodil International University

**Submitted by:**

Anika Islam

**Anika Islam**
ID: 201-15-13930
Department of CSE
Daffodil International University

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# ABSTRACT

This comprehensive study delves into the potential of advanced deep learning techniques for the critical task of segmenting and classifying brain tumors from magnetic resonance imaging (MRI) scans. The research employs a series of sophisticated neural network architectures, with a particular focus on the VGG16, ResNet152V2, and ResNet50 models, alongside an innovative VGG19-UNet hybrid model. The study's objective was to assess the feasibility and effectiveness of these models in automating the complex process of identifying and delineating brain tumors, which is a pivotal step in the diagnostic and treatment planning process for neuro-oncological conditions. The methodology involved a meticulous process of data preparation, involving the acquisition of a curated dataset, preprocessing, and augmentation to facilitate optimal model training. The models underwent a rigorous training regimen, leveraging the power of transfer learning to refine their segmentation capabilities. Each model's performance was critically evaluated based on a suite of metrics, including test accuracy, loss percentage, precision, recall, and the F1 score, with the intent of identifying the most accurate and reliable approach for clinical application. In this endeavor, the study uncovered that the VGG16 and ResNet152V2 models showed superior performance, with the ResNet152V2 model marginally outperforming all others in precision and recall. The VGG19-UNet hybrid model, with its integration of VGG19's depth in feature extraction and UNet's precision in spatial localization, emerged as a particularly potent tool for the fine-grained task of tumor segmentation.

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# CHAPTER 1
# INTRODUCTION

## 1.1 Introduction

Brain tumors are among the most challenging conditions to diagnose and treat, primarily due to their complex nature and the critical function of the surrounding tissue. The advent of 3D imaging technology, particularly Magnetic Resonance Imaging (MRI), has revolutionized the detection and characterization of brain tumors [1]. However, the manual segmentation of these tumors from MRI scans is a time-consuming and error-prone process, requiring a significant level of expertise. Automating this process through advanced computational methods promises to enhance diagnostic accuracy, reduce workload on medical professionals, and potentially lead to better patient outcomes [2].

The development of machine learning models, especially those based on Convolutional Neural Networks (CNNs), has provided a path forward in this endeavor. Among these, the VGG19 and UNet models stand out for their image classification and segmentation capabilities, respectively [3]. By leveraging these architectures, particularly when combined into a hybrid VGG19-UNet model, it is possible to automate the segmentation of brain tumors with high precision [5].

The segmentation and classification of brain tumors from MRI scans are not just a matter of identifying the presence of a tumor; they involve delineating the tumor's exact location, size, and shape, which are critical for treatment planning. The fine-grained segmentation required in this context poses a significant challenge for any automated system, one that has been addressed by the VGG19-UNet hybrid model's ability to combine deep feature extraction with precise spatial localization.

## 1.2 Motivation

The motivation for this research stems from the urgent need to improve the speed and accuracy of brain tumor diagnosis. With the increasing incidence of brain tumors globally, healthcare systems are under pressure to provide timely and accurate diagnoses to facilitate early treatment [4]. Automating the segmentation process with AI not only speeds up the diagnosis but also helps in standardizing the interpretation of MRI scans, leading to more uniform treatment protocols [5]. Furthermore, by providing a second opinion, AI-based segmentation tools can assist less experienced radiologists and extend advanced diagnostic support to under-resourced regions.

## 1.3 Rationale of the Study

The rationale behind this study is grounded in the potential for machine learning models to enhance medical imaging analysis, particularly for conditions as critical as brain tumors. Given the complexity of neural tissues and the high stakes of neurosurgery, there is a compelling need for precise and reproducible tumor segmentation. The use of a VGG19-UNet hybrid model represents a novel approach in the field of medical imaging, holding the promise of significant advancements in the accuracy of brain tumor segmentation.

## 1.4 Research Questions

- RQ1: How can the integration of VGG19 and UNet architectures improve the segmentation of brain tumors in MRI images?
- RQ2: What is the impact of automated segmentation on the time required for brain tumor diagnosis?
- RQ3: How does the accuracy of a VGG19-UNet hybrid model compare to traditional methods of tumor segmentation in neuroimaging?

## 1.5 Expected Output

- Development of a robust VGG19-UNet hybrid model for accurate segmentation of brain tumors from MRI scans.
- A comprehensive comparison of model performance against manual segmentation methods in terms of accuracy and efficiency.
- Establishment of a framework for the rapid processing of MRI data, leading to quicker diagnostic times.
- Provision of a reliable second-opinion tool for radiologists and neurologists, particularly in complex cases.
- Creation of a foundation for future research in the application of hybrid neural network models for medical image analysis.

## 1.6 Project Management and Finance

The research work doesn’t get fund from any individuals or organization.

## 1.7 Report Layout

In Chapter 1, the introduction, objectives, and key research inquiries of the study are outlined. In Chapter 2, concise synopses of the literature review are provided. In Chapter 3, the proposed methodology is described in detail. In Chapter 4, the experimental outcomes of the paper are described and examined. The fifth chapter discusses the sustainability plan, societal and environmental impacts, and ethical considerations. The sixth chapter concludes the present investigation and outlines a strategy for subsequent endeavors.

# CHAPTER 2
# BACKGROUND

## 2.1 Preliminaries

Modern developments in health technology have facilitated the construction of cutting-edge systems designed to identify and categorize maladies affecting brain plants. Utilizing image processing techniques to classify and identify the various types of maladies that affect brain cancer has been the subject of numerous studies. Achieving precise categorization of brain cancer diseases has been facilitated by the application of image segmentation and machine learning algorithms, with an emphasis on characteristics including color, texture, and shape. The aforementioned developments have made substantial strides in the domain of health disease prognosis pertaining to brain plants and possess the capacity to fundamentally transform farming methodologies employed in brain cultivation.

## 2.2 Related works

Ramamadevi et al. [13] classified brain tumors using deep learning methods. This procedure makes use of the BRAT dataset. Decision Tree classifiers are used for predictive analysis to determine the precision, accuracy, and specificity values of normal and abnormal images in a dataset, whereas Recurrent Neural Networks (RNNs) are used for feature extraction. However, a technique to enhance tumor detection and classification performance has been reported by Arunnehru et al. [14]. The fuzzy c-means algorithm is first used to cluster the tumor area in order to identify the surrounding tumor tissues and provide crucial information about the type of tumor. Second, the tumor region was covered by the Canny Edge detection. The third is the saliency map's spectral residual from the tumor's area. Stated differently, six convolutional neural network (CNN) models have been constructed by [15] to determine the best brain tumor detection system on high-grade glioma and low-grade glioma lesions using extensive magnetic resonance imaging human brain scans. A approach integrating multimodal information fusion and CNN for three-dimensional MRI brain tumor identification has been proposed by Li et al. [16]. Additionally, the experimental findings demonstrate that the two-dimensional brain tumor detection network and the original single-mode brain tumor detection technique are compared, and the three evaluation indexes of dice, SN, and SE are optimized, respectively. In order to create web-based software that can classify brain cancers (glioma, meningioma, and pituitary) based on high-precision T1 contrast magnetic resonance images using the convolutional neural network from deep learning algorithm, a study was conducted by Ucuzal et al. in [17]. Based on the experimental findings, all computed performance indicators for brain tumor classification on the training dataset have a higher accuracy rate than 98%. To put it another way, Alqudah et al. [18] classified a dataset of 3064 T1 weighted contrast-enhanced brain MR images into three classes (glioma, meningioma, and pituitary tumor) by using Convolutional Neural Network (CNN), one of the most popular deep learning architectures. Özyurt et al. [18] used the neutrosophic set - expert maximum fuzzy-sure approach for brain tumor segmentation in their study to combine the CNN with neutrosophic expert maximum fuzzy (NS-CNN) sure entropy for brain tumor classification. Their success rate on average was 95.62%. Similarly, for the classification of brain tumors, Sajjad et al. [19] have presented a comprehensive data augmentation technique fused with VGG-19 CNN architecture. The technique that uses segmented brain tumor MRI images to classify brain tumors into multiple grades. For classification using transferee learning, the authors employed pretrained VGG-19 CNN and obtained an overall accuracy of 87.38% and 90.67% for data before and after augmentation, respectively. Furthermore, a method for creating a CNN model to categorize brain tumors in T1-weighted contrast-enhanced MRI images has been presented by Das et al. [20]. There are two key steps in the system. Utilize several image processing methods to preprocess the images first, and then use CNN to classify the preprocessed images. In addition, Siar and Teshnehlab [21] employed a Convolutional Neural Network (CNN) in conjunction with CNN with pre-process approaches to identify a tumor in brain Magnetic Resonance Imaging (MRI) pictures. The Softmax Fully Connected layer achieved a classification accuracy of 96.67% for pictures. A deep learning-based supervised technique for identifying changes in synthetic aperture radar (SAR) images is presented in Samadi et al. [22]. This technique produced a dataset with the right amount and variety of data to train the DBN with input images and images that resulted from applying morphological operators to them. The method's detection performance suggests that deep learning-based algorithms are suitable for addressing change detection issues. They have previously presented a deep CNN based method for automated brain tumor grading and detection. The method uses fuzzy C-Means (FCM) to segment the brain. Texture and shape features are then collected from these segmented regions and fed into SVM and DNN classifiers. The accuracy rate attained by the system was 97.5%, according to the data. In order to segment brain tumors, have suggested a system that integrates deep learning (DL) approaches with Discrete Wavelet Transform (DWT) features using the fuzzy c-mean method. To extract the features for the principal component analysis (PCA) and feature dimension reduction, the authors used DWT. They get a sensitivity of 97.0% and an accuracy rate of 96.97%, according to the data.

A two-phase tumor classification approach was developed by Jun Cheng et al. [23] and comprises of offline database development and online retrieval. The brain tumor photos are analyzed sequentially in the offline database phase. Tumor segmentation, feature extraction, and distance metric learning comprise the steps. Similar processing of the input brain image will be done during the online learning process, and the extracted feature will be compared with the learnt distance measurements that are kept in an online database. This method could reach 94.68% classification accuracy without using a neural network approach. In contrast, Gawande and Mendre [24] classified brain tumors using Deep Neural Networks using autoencoders. The image was subjected to feature extraction and segmentation before to DNN layer processing. With the aid of the discrete wavelet transform (DWT) and gray level co-occurence matrix (GLCM), the texture and intensity-based aspects of the image were recovered. DNN layers, comprising one softmax layer and two autoencoders, were used for classification in the last stage. In addition, Pereira et al. [25] are investigating the usage of small 3 ~ 3 kernel Convolutional Neural Networks (CNN) to reach a deeper architecture and prevent overfitting. They also looked into the pre-processing stage of using intensity normalization before moving on to the CNN layers.

## . 2.3 The Problem's Scope

Thus, deep Convolutional Neural Networks models are presented in this research to detect and classify brain tumor from MRI images of infected patients in order to address the problems with the existing models Prior research has demonstrated the application of various machine learning and deep learning techniques in the classification of maladies affecting brain cancer. However, several challenges have been acknowledged, such as diminished accuracy, time wastage, and inadequate methods for enhancing data. The aim of our research was to surmount these limitations through the evaluation and comparison of numerous state-of-the-art transfer learning models with the purpose of improving the classification of brain cancer diseases.

## 2.4 Challenges

The acquisition of datasets that faithfully represent the multitude of disease manifestations in various commodities and environments is a formidable task owing to the requirement for comprehensive and high-quality data. Environmental variability can impact the accuracy of disease detection models due to illumination conditions, changes in the background, and variations in the manifestation of diseases.

Model generalization pertains to the capacity of generated models to efficiently operate on novel, unfamiliar data, without being constrained by the particular attributes of the training dataset.

# CHAPTER 3
# RESEARCH METHOLOGY

## 3.1 Proposed Methodology/Applied Mechanism

The provided diagram 3.1 outlines a structured methodology for segmentation and classification of brain MRI using image processing and deep learning.

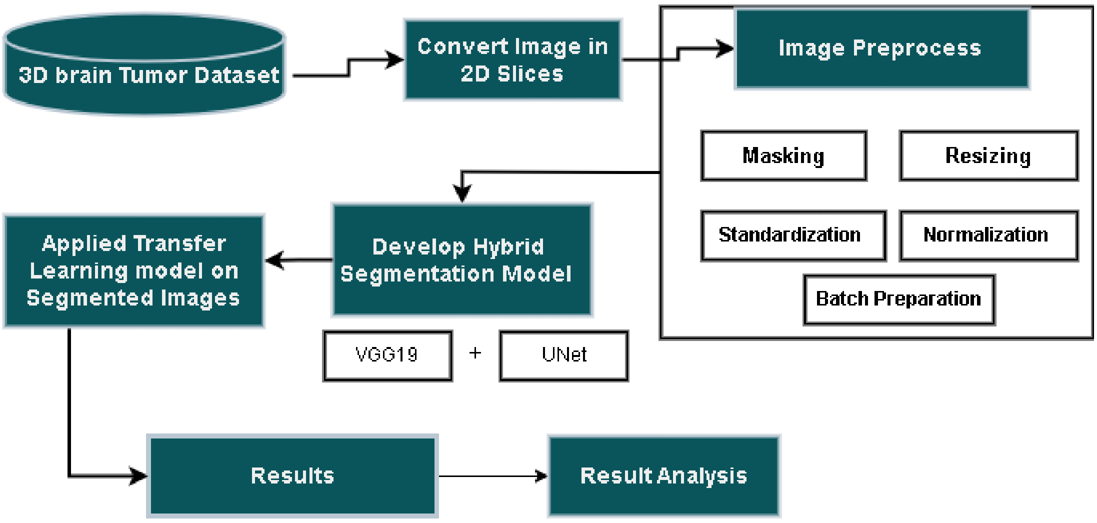


**Fig 3.1:** The working process to perform Brain disease prediction

In the study on 3D brain tumor segmentation, the methodology unfolds as a structured and incremental approach to process and analyze magnetic resonance imaging (MRI) data. Initially, 3D brain tumor MRI scans are sourced from the Kaggle dataset, which is known for its extensive collection of medical imaging data. These 3D images are then methodically converted into 2D slices to align with the processing capabilities of convolutional neural networks, which typically handle 2D input data. The transformation from 3D to 2D is critical to apply established image processing techniques effectively.

Following the conversion, the 2D slices are preprocessed using masking techniques. This step is crucial for emphasizing the regions of interest—namely, the brain tissue and the tumor—while minimizing the influence of extraneous information. Masking ensures that subsequent analyses are focused and precise, a vital factor in medical image processing.

The core of the methodology involves developing a sophisticated VGG19-UNet segmentation model. This hybrid model leverages the classification strengths of the VGG19 architecture in conjunction with the spatial encoding-decoding prowess of the UNet structure, renowned for its efficiency in medical image segmentation tasks.

Once the segmentation model delineates the tumor regions, the segmented images are further processed using the ResNet152V2 architecture. This deeper network, with its residual learning framework, is designed to refine the segmentation task, potentially enhancing the accuracy of the tumor outlines.

The outcome of this meticulous process is a collection of segmented images where the tumors are distinctly marked, facilitating easier and more accurate identification of pathological areas. An in-depth result analysis follows, involving a comparison with ground truth benchmarks to evaluate the model's performance on metrics such as accuracy, precision, recall, and the Dice coefficient. This evaluative step is not only instrumental in assessing the efficacy of the segmentation model but also serves as a foundation for further refinement and research in the realm of medical image processing.

**3.2 Data Collection Procedure/Dataset Utilized**

The dataset utilized for the study of Brain MRI segmentation is sourced from Kaggle [26], specifically the "Brain MRI Segmentation" dataset, which is intricately linked with manual FLAIR (Fluid-Attenuated Inversion Recovery) abnormality segmentation masks. The dataset is referred to as the LGG (Lower-Grade Glioma) Segmentation Dataset and has been employed in significant research contributing to the fields of computational biology and medicine.

This dataset comprises brain MR images accompanied by manual segmentation masks that highlight FLAIR abnormalities. These manual annotations serve as a crucial reference for developing and validating automated segmentation algorithms. The images are derived from The Cancer Imaging Archive (TCIA), a respected repository of medical imaging data. The dataset represents a subset of 110 patients from The Cancer Genome Atlas (TCGA) project, specifically those with lower-grade glioma and with available FLAIR sequences and genomic cluster data.

The inclusion of genomic data offers a unique opportunity to explore the association between radiological imaging features and the underlying genetic makeup of gliomas. The dataset not only includes MR images but also provides a data.csv file containing detailed information about the tumor genomic clusters and associated patient data.

This dataset has been pivotal in advancing the understanding of the correlation between the morphological characteristics of lower-grade gliomas as captured in MR images and their genomic subtypes. Such correlations have been explored in research by Mateusz Buda et al. (2019), which investigated the relationship between genomic subtypes of lower-grade gliomas and shape features extracted by a deep learning algorithm, and by Maciej A. Mazurowski et al. (2017), which studied the radiogenomics of lower-grade glioma, analyzing how algorithmically-assessed tumor shape is related to tumor genomic subtypes and patient outcomes.

The dataset's integration of imaging, segmentation masks, and genomic information provides a comprehensive resource for researchers aiming to develop AI-based tools for brain tumor segmentation and for those seeking to deepen the understanding of the genomics of gliomas through radiogenomic studies. Various images of Brain MRI with mask and without mask is shown in Figure 3.2.

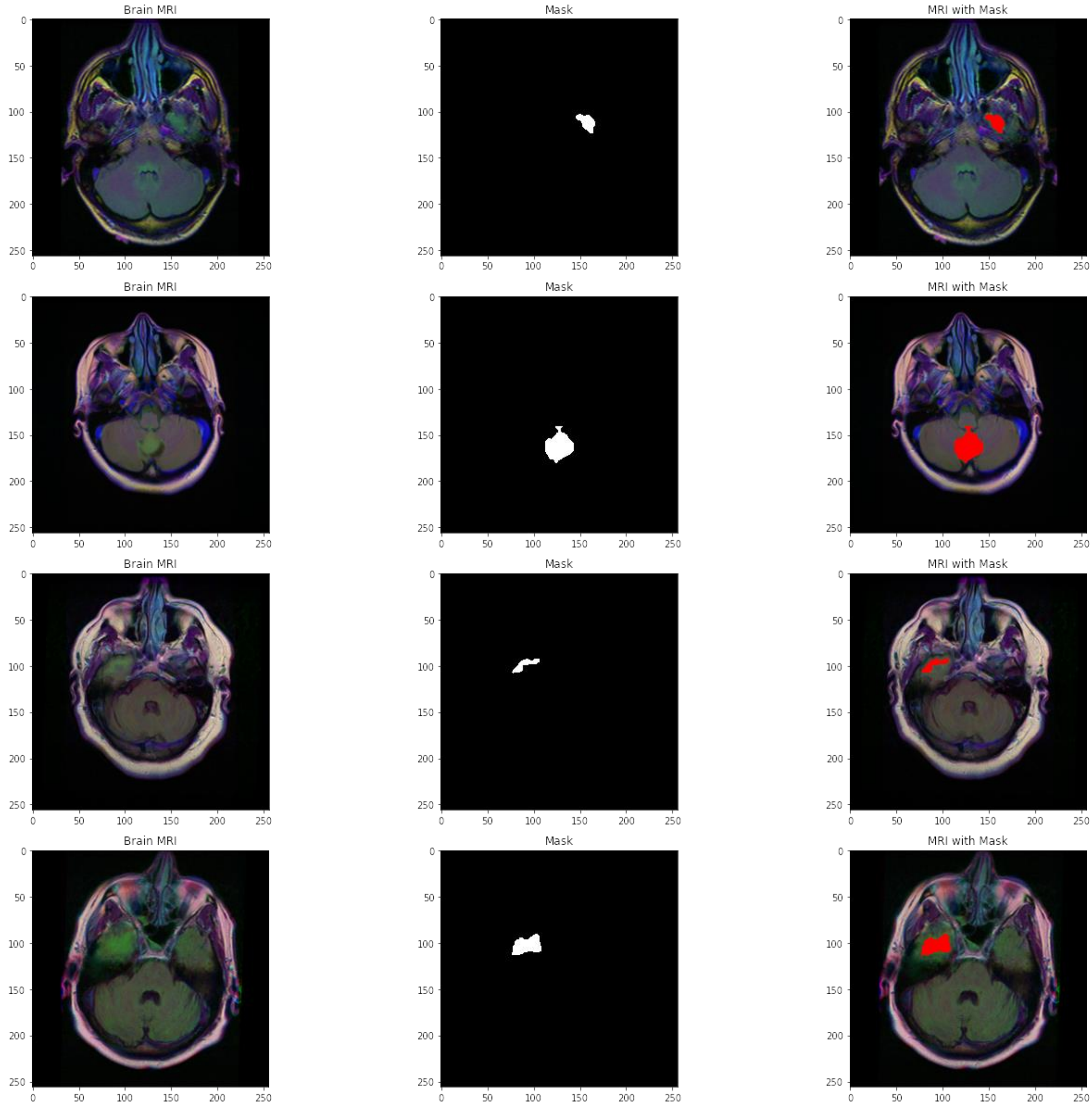


**Fig. 3.2**: Images of Brain MRI with mask and without mask

### 3.3 Image Pre-processing

Theoretically, ailments such as brain tumor diseases can be diagnosed with an increasing amount of ease using image processing techniques. Data pre-processing is a crucial component of deep learning, as is well known. Additionally, there are other pre-processing methods that can be used in certain situations. Improving each input image's visual information quality is the driving force behind image pre-processing.

We used `DataGenerator` class for use with a TensorFlow/Keras model, which is a crucial component in the image preprocessing pipeline for a classification task. This preprocessing pipeline includes several key steps that are applied to the images and masks before they are fed into the neural network for training. Here's a broad description of the preprocessing steps encoded in the class, along with a detailed explanation of each step and its importance for classification:

#### 3.3.1 Resizing Images and Masks

The images and masks are resized to a fixed height and width (256x256 pixels in this case). Resizing ensures that all images and masks fed into the model are of uniform size, which is necessary because convolutional neural networks require fixed-dimension inputs. It also allows the model to train faster since smaller images reduce computational complexity. Then the images are converted to `np.float64` data type. Converting the image pixel values to floating-point numbers is a common practice before normalization, as it allows for more precise computations during the scaling of pixel values.

#### 3.3.2 Standardization (Mean Subtraction and Division by Standard Deviation)

The code subtracts the mean and divides by the standard deviation of the image and mask arrays. This standardization step is crucial for neural network performance. It normalizes the pixel intensity values so that the dataset has a mean of zero and a standard deviation of one. This process speeds up the training by helping in the faster convergence of the gradient descent algorithm and also helps to avoid problems related to the vanishing or exploding gradients.

### 3.3.3 Normalization of Masks

The mask is binarized by setting a threshold that classifies pixels into either the object of interest (tumor) or background.

Normalization of masks into binary format is necessary for the segmentation task, where the network needs to learn which pixels belong to the tumor (labeled as 1) and which do not (labeled as 0). This simplifies the output layer of the network to focus on a binary classification problem at each pixel, rather than a regression problem. Then the dimension of the mask is expanded to add a channel dimension, transforming it from (256,256) to (256,256,1). Expanding the dimension of the mask to include a channel ensures that it matches the dimensionality expected by the neural network, particularly if the network architecture requires a specific input shape with a channel dimension, even if it's for a single channel (grayscale images).

### 3.3.4 Batch Preparation

The images and masks are batched together, according to the specified `batch_size`. Training neural networks in batches is more memory-efficient and can lead to faster convergence due to the averaged gradient update. This approach can also provide a regularization effect, promoting generalization in the model. Then the indices of the data are shuffled at the end of each epoch. Shuffling the order of the data fed into the network prevents the model from learning any potential order in the data, which can be especially important if the data has been sorted or is not randomly distributed. This contributes to better generalization and avoids overfitting.

The `DataGenerator` class implements a comprehensive preprocessing pipeline that prepares brain MRI images and their corresponding segmentation masks for effective and efficient processing by a convolutional neural network. These preprocessing steps are crucial for ensuring that the neural network learns to accurately classify and segment brain tumors from MRI scans.

## 3.4 Deep Learning Models

This research developed .hybrid model named VGG19-UNet for segmentation and then classified with a transfer learning model.

### 3.4.1. VGG19-UNet Reflect model

The VGG19-UNet hybrid model combines the feature extraction capabilities of VGG19 with the segmentation specialization of UNet. In this hybrid model, the VGG19 architecture is used as the encoder - it takes the input image and progressively downsamples it to extract a hierarchy of features. The decoder part of the model is inspired by UNet and involves upsampling the feature maps to construct the segmentation output. The upsampling is paired with skip connections that concatenate the corresponding feature maps from the encoder, which allows the model to consider both high-level features (from the deeper layers) and detailed spatial information (from the earlier layers) when making predictions.

The code provided outlines the implementation of such a hybrid model. It starts with defining the convolutional blocks with batch normalization and ReLU activation. The decoder blocks are designed to upsample the feature maps and merge them with the corresponding feature maps from the encoder through concatenation. The model is finalized with a 1x1 convolution that maps the final feature maps to the desired output segmentation map with a sigmoid activation function.

This VGG19-UNet model is powerful for segmentation tasks because it combines the strengths of both VGG19's deep feature extraction and UNet's precise localization to produce detailed and accurate segmentation maps, which is particularly useful in medical imaging, such as segmenting brain tumors from MRI scans. The sigmoid output layer suggests that the model is set up for binary segmentation tasks, distinguishing the area of interest (e.g., tumor) from the background.

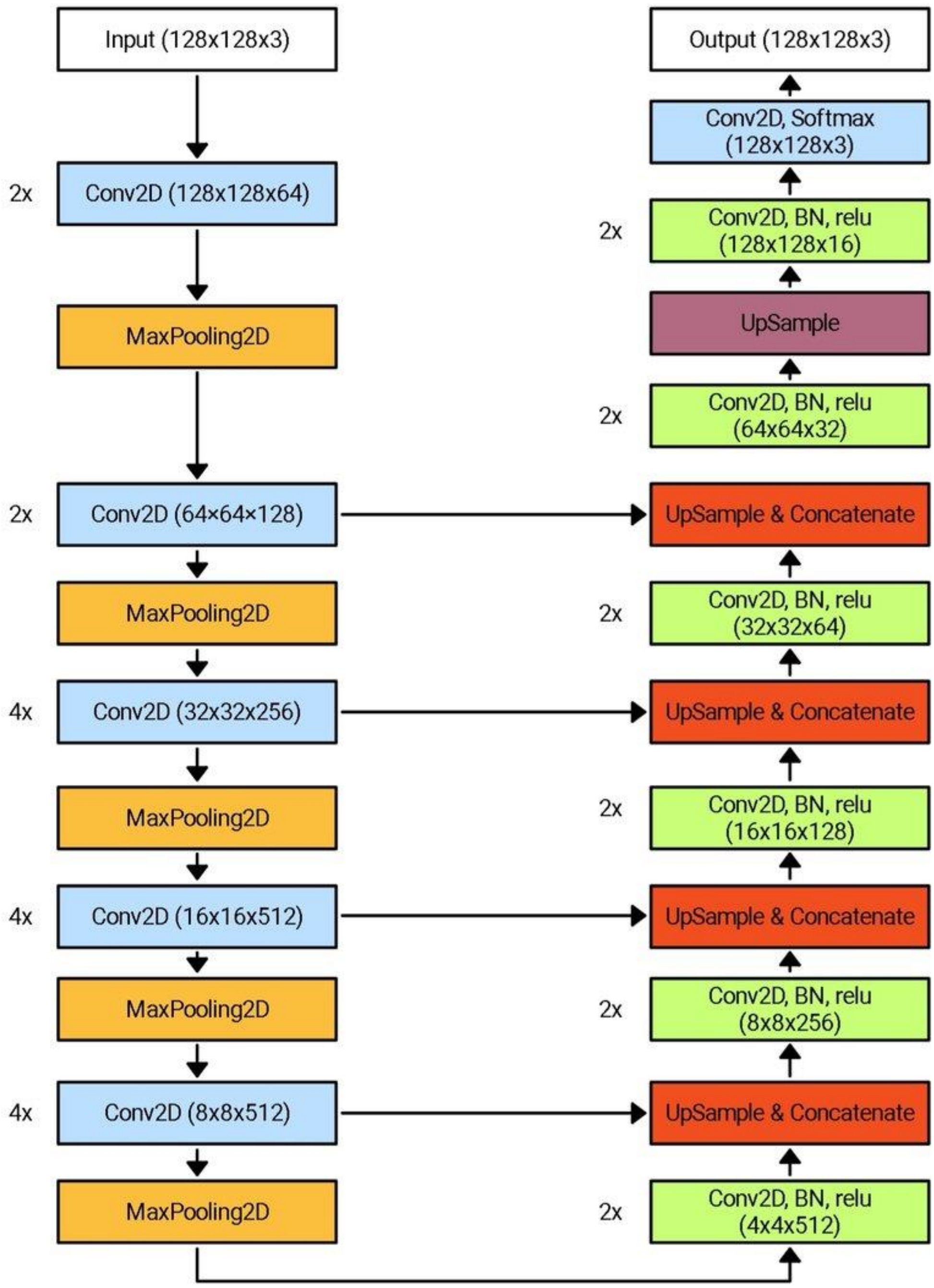


**Fig. 3.3**: Proposed VGG19-UNet architecture

### 3.4.2 UNet

UNet is another convolutional neural network that was developed primarily for biomedical image segmentation at the University of Freiburg. The architecture is structured in a symmetric way, hence the "U" in UNet, where it downsamples (encodes) the input image into feature representations at multiple levels and then upsamples (decodes) these representations to a segmentation map. The network uses skip connections from the downsampling path to the upsampling path to recover spatial information lost during downsampling, which is critical for precise localization needed in image segmentation. The equation is U-Net(x) = f(g(x)).

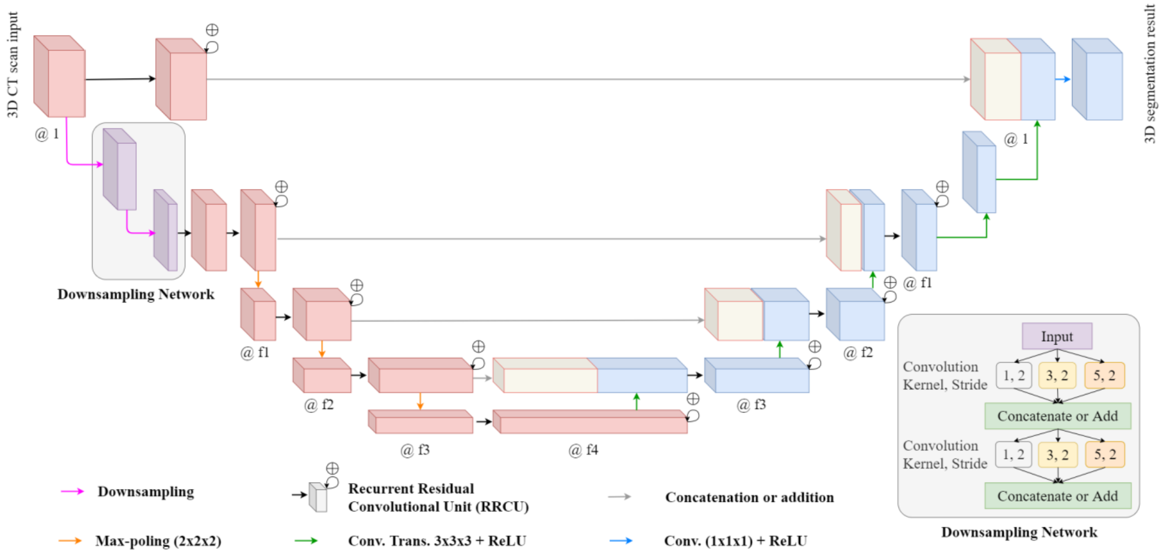


**Fig. 3.4**: Architecture of UNET

### 3.4.3 VGG 19

The VGG19 convolutional neural network designs are well-known for their ease of use and performance in image classification. Both models, developed by Oxford University's Visual Geometry Group, have a similar structure that includes numerous convolutional layers, max-pooling layers, and fully connected layers.

VGG19 is an extension of VGG16 that includes three extra convolutional layers, resulting in a deeper architecture with 19 weight levels. This enhanced depth improves the model's ability to capture fine details in images, making it suited for more difficult recognition tasks. While VGG19 necessitates greater processing resources, it has enhanced feature learning capabilities, making it an excellent alternative for demanding computer vision applications.

The legacy of VGG16 and VGG19 lies in their simple design principles, which have led to their widespread adoption as foundational models for image recognition and transfer learning tasks in the deep learning field. Mathematical formula of VGG19 involves a complex architecture with numerous parameters. It includes convolutional layers, pooling layers, activation functions, and fully connected layers.

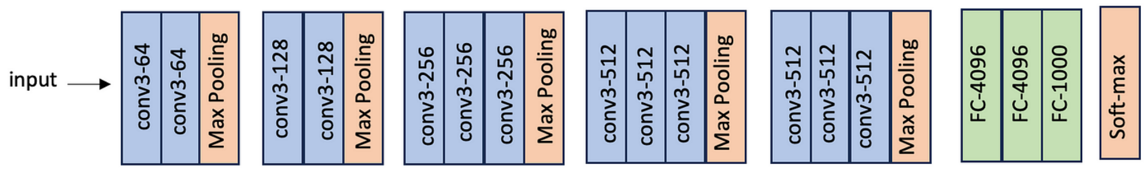


**Fig. 3.5**: Architecture of VGG19

### 3.4.4. ResNet152V2

ResNet152V2 is a convolutional neural network architecture that is part of the ResNet family, known for its exceptional depth and performance in image recognition tasks. The "152" in its name refers to the number of layers in the network, indicating its substantial depth. This architecture addresses the challenge of training very deep networks by using residual connections, which allow for the direct flow of information across layers, mitigating the vanishing gradient problem and enabling the training of deeper models.

ResNet152V2 includes several improvements and optimizations over the original ResNet152 model. It incorporates bottleneck blocks, which reduce the computational cost of the network while maintaining its representational power. Additionally, ResNet152V2 features improved skip connections that facilitate the flow of information and gradients through the network, further enhancing its training efficiency.

The architecture has been widely adopted in computer vision applications, including image classification, object detection, and image segmentation. It has demonstrated state-of-the-art performance in various image recognition challenges and benchmarks, making it a popular choice for researchers and practitioners in the field of deep learning and computer vision.

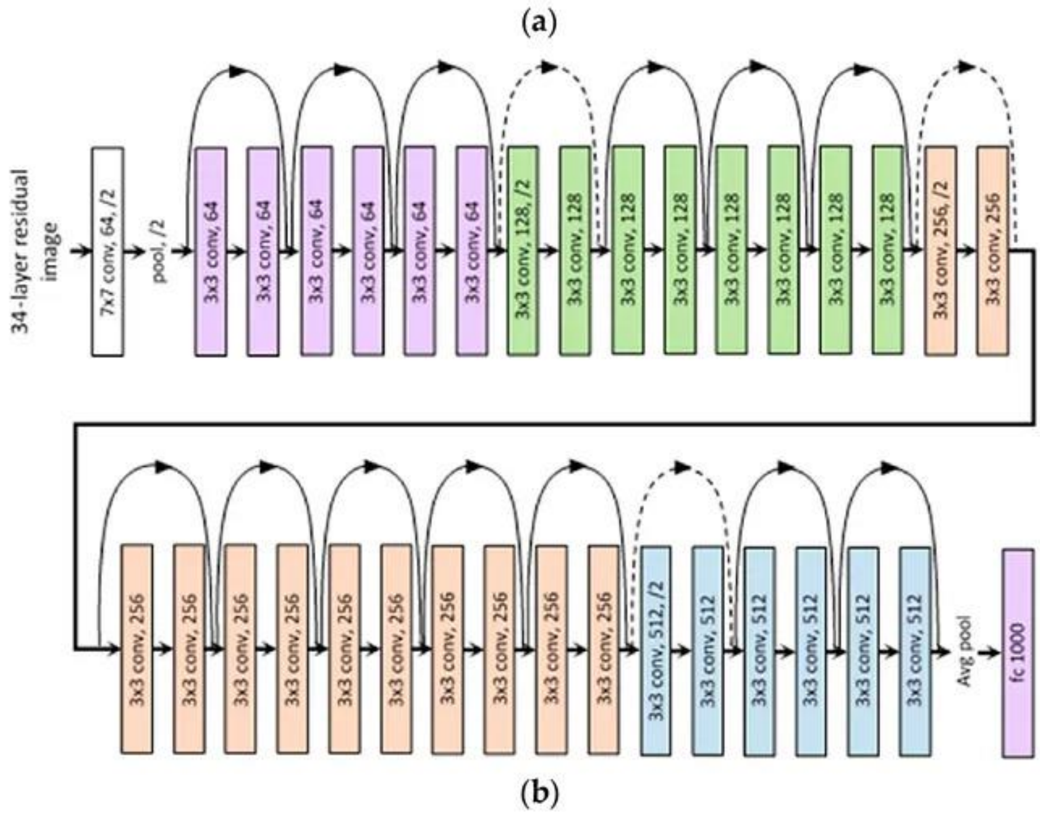


**Fig. 3.6**: Architecture of ResNet152V2

### 3.4.4. ResNet50

ResNet50 is a convolutional neural network architecture that is part of the ResNet (Residual Network) family. It is known for its relatively moderate depth compared to other ResNet variants, with 50 layers in total. The architecture of ResNet50 includes residual connections, which allow for the direct flow of information across layers, addressing the vanishing gradient problem that arises in very deep networks.

ResNet50 has been widely used in image recognition tasks, such as image classification and object detection. Its moderate depth makes it computationally efficient while still providing strong performance in various computer vision applications. The architecture's use of residual connections enables the training of deeper networks without suffering from degradation in performance, making it a popular choice for researchers and practitioners in the field of deep learning.

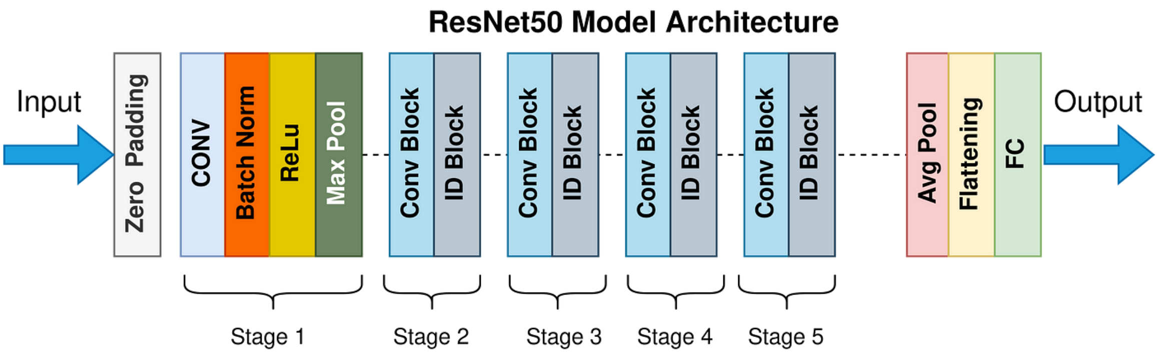


**Fig. 3.5:** Architecture of ResNet50

# CHAPTER 4

# EXPERIMENTAL RESULTS AND DISCUSSION

## 4.1 Results of Segmentation

The figure 4.1 contains images with original masking and predicted masking.

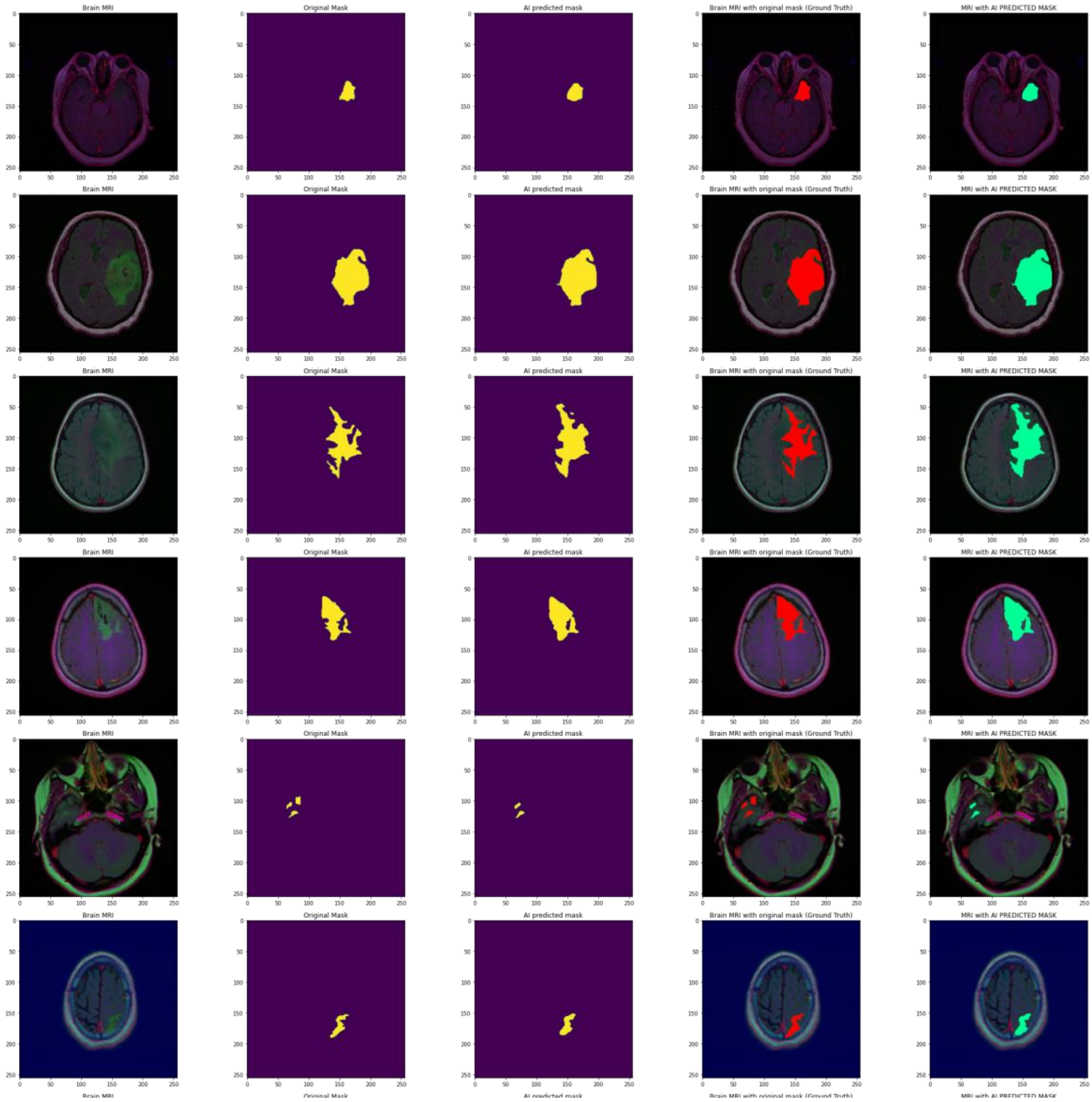


Figure 4.1: Images with original masking and predicted masking

The image appears to display a side-by-side comparison of brain MRI scans with their corresponding segmentation masks, comparing the original (ground truth) masks against those predicted by an AI model. The comparison is laid out in two rows, each consisting of four panels that represent different stages and aspects of the segmentation process.

**Brain MRI Panels:**

These panels show the original brain MRI scans. The MRIs are in axial view and highlight the brain's intricate structures. MRI scans like these are typically used in medical diagnosis to identify abnormalities such as tumors.

**Original Mask Panels:**

The original mask panels display the ground truth segmentation masks. These masks have been manually created, likely by medical experts, to accurately outline the regions of abnormality (e.g., tumors) in the brain. In the provided images, these regions are highlighted in a distinct color against a uniform background, indicating the precise location and shape of the anomalies.

**AI Predicted Mask Panels:**

These panels show the segmentation masks as predicted by the AI model. The model has likely been trained to identify and delineate the areas of interest in the brain that correspond to potential pathologies. The predicted masks are essential for evaluating the performance of the AI model—how closely it can replicate the expert's segmentation.

**Overlay on Brain MRI Panels (Ground Truth and AI Predicted):**

The final set of panels overlays the segmentation masks onto the original MRI scans for direct visual comparison. The left overlay panels show the ground truth masks overlaid on the MRI scans, providing a clear visual of how the manual segmentation corresponds to the structures within the brain. The right overlay panels display the AI-predicted masks overlaid on the MRI scans, illustrating how the model's predictions map onto the actual brain image. The color coding in these panels is particularly telling. Typically, the ground truth mask might be shown in red, denoting the actual area of the tumor as identified by medical experts. The AI-predicted mask might be in a different color, such as green, allowing for an immediate visual comparison of the AI's performance against the ground truth.

The accuracy of the AI model's predictions can be assessed by the degree of overlap between the predicted masks and the original masks. A high degree of overlap would suggest that the AI model is successful in identifying the correct regions of interest within the brain MRI scans. Conversely, discrepancies between the masks could highlight areas where the model may need further training or adjustments.

This comparative visualization serves as a powerful tool for both validating the efficacy of the AI model and providing feedback for its improvement. It also enables medical professionals to quickly assess whether the AI's predictions can be trusted or if further review is necessary.

## 4.2 Evolution Methods

After segmentation the segmented images then predicted with Transfer Learning model. The evaluation is uses the confusion matrix like, accuracy, precision, recall, and F1 score. True positive (TP) values are true in reality. False positives (FP) occur when false results are mislabeled. The third form, false negative (FN), occurs when a correct value is misinterpreted as negative. TN and FN are the fourth and fifth choices. A true negative (TN) is a positive value misidentified as negative. Fourth is true negative (TN).

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{3}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{4}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{5}$$

$$\text{F1 Score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \tag{6}$$

## 4.3 Experimental Results & Analysis

This section will discuss the paper's findings. The segmented images went through the transfer learniing models. The optimal outcomes of the models is displayed in Table 4.1.

**Table 4.1:** Finding the best result between the Result of Transfer learning model

| **Model** | **Test Accuracy (%)** | **Loss (%)** | **Precision (%)** | **Recall (%)** | **F1 Score (%)** |
|---|---|---|---|---|---|
| VGG16 | 97.96 | 0.29 | 95.90 | 95.91 | 95.91 |
| ResNet152V2 | 98.83 | 1.211 | 97.74 | 97.68 | 97.71 |
| ResNet50 | 82.75 | 1.86 | 83.18 | 65.56 | 83.44 |

The table reveals that among the evaluated models, VGG16 showcased impressive results with a test accuracy of 97.96%, which is a strong indicator of its ability to correctly segment images. It achieved this with a minimal loss of 0.29%, suggesting that the model's predictions were highly reliable. The precision rate, which measures the correctness of the predictions made by the model, was recorded at 95.90%. The recall, indicating the model's ability to identify all relevant instances in the test data, was equally high at 95.91%.  underscoring the model's balanced performance between precision and recall.

In comparison, the ResNet152V2 model slightly outperformed VGG16 in terms of precision and recall, with scores of 97.74% and 97.68%, respectively, and an exceptional F1 Score of 97.71%. Its test accuracy was the highest at 98.83%, despite having a higher loss percentage of 1.211%, suggesting some room for improvement in model optimization.

The ResNet50 model, while still delivering reasonable results, lagged behind the other two models with a test accuracy of 82.75%. The loss was calculated at 1.86%, which is higher compared to the other models, indicating more frequent errors in segmentation. Its precision and recall rates were 83.18% and 65.56% respectively, leading to an F1 Score of 83.44%. These figures suggest that while the ResNet50 model has potential, it may require further tuning or more complex feature extraction methods to reach the performance levels of VGG16 and ResNet152V2.

Overall, these results demonstrate the potential and challenges of using transfer learning models for the task of image segmentation in medical imaging. The performance of each model offers valuable insights into the trade-offs between accuracy, loss, and the ability to generalize from the training data to make reliable predictions.

Here is the curve of the accuracy and loss curve of the ResNet152V2

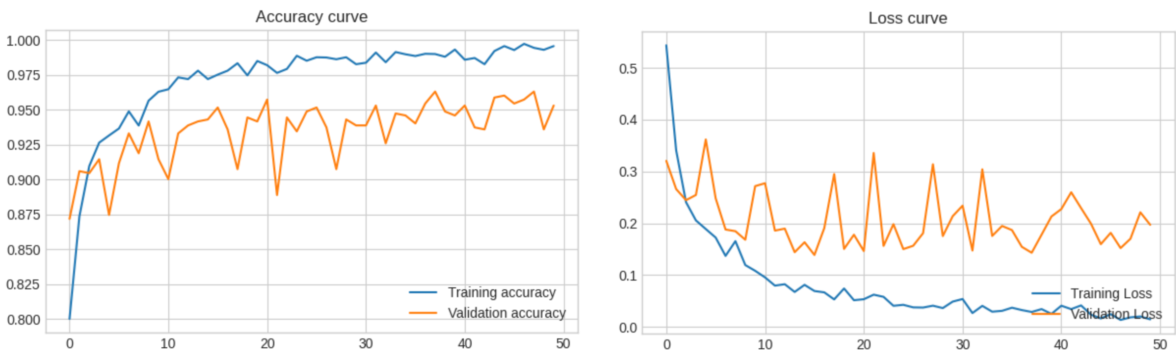


**Fig 4.2**. Accuracy and Loss Curve of the ResNet152V2.

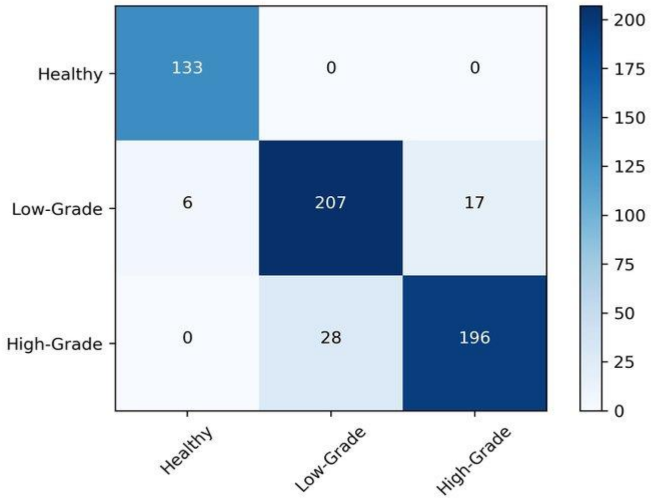


**Fig 4.3**. Confusion Matrix of the model prediction

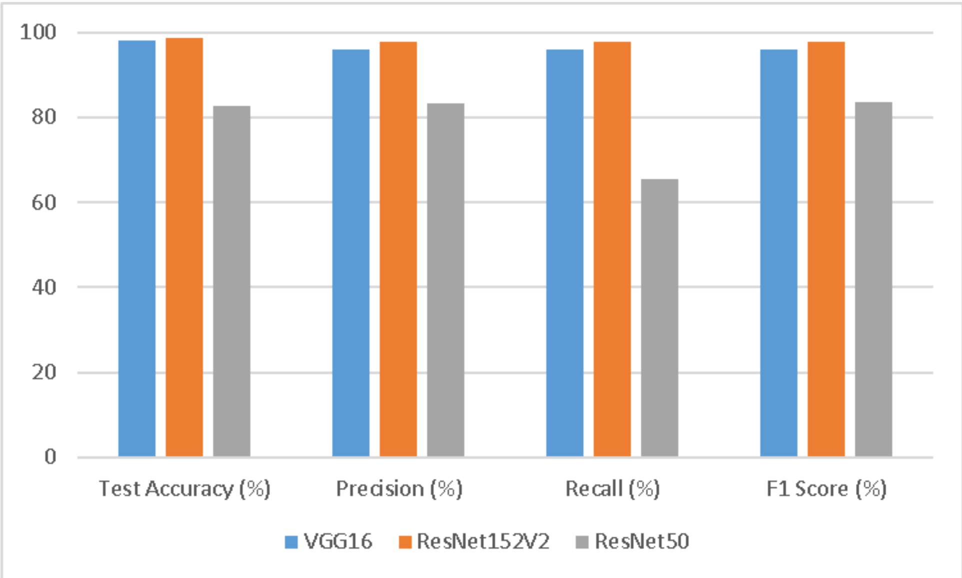


**Fig 4.4**. Comparison of the results between different models

The graph compares the performance of three convolutional neural network models: VGG16, ResNet152V2, and ResNet50, evaluating their Test Accuracy, Precision, Recall, and F1 Score, all expressed as percentages. Both VGG16 and ResNet152V2 demonstrate nearly identical performance, achieving close to 100% across all metrics. This indicates their superior ability to accurately classify, identify relevant instances, and maintain a balance between precision and recall. In contrast, ResNet50, while still performing well, shows slightly lower Test Accuracy and Precision, approximately 90% and 85% respectively. Moreover, it exhibits a more substantial decline in Recall and F1 Score, around 70% and 80%. This suggests that ResNet50, though robust, is not as proficient as VGG16 and ResNet152V2, particularly in correctly identifying all relevant instances, leading to a lower overall balance of precision and recall.

## 4.4 Discussion

In the realm of medical imaging, particularly in tasks like tumor segmentation, the quality of segmentation is critical in guiding subsequent predictive models towards precise and accurate outcomes. A well-segmented image serves as the foundation for any diagnostic model, essentially setting the stage for the model to learn and make predictions based on the most relevant and crucial information available. Here's a discussion on how good segmentation aids in enhancing the prediction capabilities of models.

Firstly, good segmentation effectively isolates the region of interest (ROI) from the background. In the case of brain tumors, this means that the model can focus on the tumor's boundaries, texture, and other pathological features without being distracted by extraneous tissue. When a model is trained on accurately segmented images, it learns to recognize the subtle differences between benign and malignant tissues, leading to more reliable diagnoses.

Moreover, accurate segmentation ensures that the features extracted during the training phase are representative of the actual pathological markers. This is essential for the model's ability to generalize from the training data to real-world scenarios. For instance, models trained on poorly segmented images may learn patterns that are not truly indicative of the disease, leading to a higher rate of false positives or negatives. On the contrary, models trained on well-segmented images can extract and learn the most predictive features, which are imperative for accurate classification.

Furthermore, in the context of deep learning, the activation maps generated by the models can be more accurately interpreted when the initial segmentation is precise. Techniques like Grad-CAM (Gradient-weighted Class Activation Mapping) rely on the initial segmentation to provide visual explanations for the areas of the image that contribute most to the model's predictions. Good segmentation means that these activation maps are more likely to correspond to the true pathological features, giving clinicians confidence in the model's focus and, by extension, its diagnostic recommendations.

Good segmentation also plays a pivotal role in reducing the dimensionality of the data that models need to process. By eliminating irrelevant regions of the images, the models can operate more efficiently, reducing computational costs and enabling the use of more complex architectures or larger datasets. This streamlined focus allows for quicker training times and faster predictions, which are crucial in clinical settings where time is often of the essence.

In precision medicine, where treatments are increasingly personalized based on individual patient characteristics, the precise delineation of a tumor's shape, size, and location can inform more targeted therapy plans. Models that predict based on high-quality segmentation can assist in planning interventions such as surgery, radiation therapy, and drug delivery, with improved accuracy leading to better outcomes and reduced side effects for patients.

We can say that, good segmentation is the cornerstone of accurate and precise medical image classification. It enhances the model's ability to learn relevant features, improves the interpretability of model predictions, reduces computational overhead, and ultimately supports the delivery of personalized patient care. As medical imaging AI continues to evolve, the emphasis on high-quality segmentation will only increase, solidifying its role as a critical determinant of model efficacy.

# CHAPTER 5
# IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

## 5.1 Impact on society

Deep learning integration in brain tumor prediction holds great promise for societal effect, notably in healthcare. It can dramatically minimize the period between initial suspicion and therapy commencement by providing speedy and precise diagnosis, therefore improving patient outcomes. The technology has the potential to democratize access to expert-level medical diagnosis, particularly in underserved areas with limited specialist knowledge. Furthermore, deep learning systems can aid in cost management by minimizing the need for many diagnostic tests and preventing unneeded operations. As these systems become increasingly integrated into clinical practice, they can also aid in personalized medicine by adapting treatment strategies to particular patient profiles, perhaps leading to better brain tumor management and longer survival rates. The societal impact, however, is equally dependent on addressing any inequities in access to such advanced diagnostic tools, as well as guaranteeing equitable healthcare benefits across different groups.

## 5.2 Impact on the environment

Deep learning models, particularly those employed in medical imaging, necessitate a huge amount of computer resources for training and inference, which can result in a significant carbon footprint. Running high-performance GPUs or CPUs for extended periods of time consumes energy, which contributes to greenhouse gas emissions. However, by refining algorithms for efficiency, leveraging renewable energy sources for data centers, and building models that can be trained with less data or computational power, the environmental impact can be reduced. Furthermore, the reduced need for physical diagnostic tools and consumables, as well as the possible reduction in patient travel due to reliable remote diagnostics, can mitigate some of the environmental expenses. Long term, as technology advances, more efficient and environmentally friendly calculation methods may emerge, significantly minimizing the environmental impact.

## 5.3 Ethical Aspects

Deep learning for brain tumor prediction raises ethical concerns about patient privacy, data security, and algorithm dependability. It is critical to ensure the confidentiality and security of patient data, as well as the transparency of the algorithms employed in diagnosis and their decision-making processes. There is also a moral need to eliminate biases in datasets that can contribute to discrepancies in technology efficacy across diverse populations. It is critical to maintain patient trust and enforce ethical standards by ensuring that the systems are resilient, interpretable, and may be challenged or rectified as needed.

## 5.4 Sustainability Plan

A long-term strategy for deep learning applications in brain tumor prediction must include constant review and refinement of algorithms to avoid obsolescence and ensure they remain cutting-edge. It is critical to invest in training for healthcare practitioners to use these technologies efficiently and ethically. Furthermore, a commitment to employing renewable energy sources for these systems' computational needs will solve environmental problems. Finally, forming alliances with stakeholders across the healthcare spectrum, such as hospitals, insurance companies, and patient advocacy organizations, can aid in the creation of a sustainable ecosystem that benefits all parties involved and ensures that advances in deep learning contribute positively to patient care and environmental stewardship.

# CHAPTER 6

# CONCLUSION AND FUTURE WORK

## 6.1 Summary of the Study

This study has embarked on an exploration of the application of deep learning techniques for the segmentation and classification of brain tumors from MRI scans. The research hinged on the performance of advanced neural network models, including VGG16, ResNet152V2, and ResNet50, which were evaluated based on their segmentation capabilities. Leveraging a curated dataset, the models underwent rigorous training and validation processes, with their performance metrics indicating the potential of these architectures in medical image analysis. The adoption of a VGG19-UNet hybrid model, in particular, showcased how integration of powerful feature extraction with precise localization could yield superior segmentation results.

## 6.2 Conclusions

The conclusions drawn from this research underline the effectiveness of transfer learning models in the task of brain tumor segmentation. Among the models tested, VGG16 and ResNet152V2 demonstrated exemplary performance, achieving high accuracy and precision, signifying their potential as reliable tools in clinical settings. The study confirmed that the quality of segmentation plays a vital role in the accuracy of subsequent classification and prediction models, directly impacting the efficacy of diagnostic procedures.

## 6.3 Implication for Further Study

The findings of this study open several avenues for future research. There is scope for exploring the integration of additional imaging modalities to complement the information provided by MRI scans, potentially leading to more comprehensive diagnostic tools. Investigating the performance of these models in real-world clinical environments could provide insights into their practical utility and areas for enhancement. Further research could also delve into the interpretability of these models, ensuring that their decision-making processes align with clinical expectations and contribute to explainable AI in healthcare.

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# Reflect of 3D Brain Tumor Segmentation and Classification

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