Deep Learning Based Brain Tumor Segmentation

(Application Project – Computer Vision)

MASTER *Optique Image Vision Multimedia* (*OIVM*)
Spécialité *Systèmes Distribués et Technologies de la data Science* (*SDTS*)

<u>Intitulé :</u>

Segmentation d'une tumeur de cerveaux

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Abstract

Brain tumor segmentation is one of the most challenging problems in medical image analysis. The goal of brain tumor segmentation is to generate accurate delineation of brain tumor regions. In recent years, deep learning methods have shown promising performance in solving various computer vision problems, such as image classification, object detection and semantic segmentation. A number of deep learning-based methods have been applied to brain tumor segmentation and achieved promising results. Considering the remarkable breakthroughs made by state-of-the-art technologies,

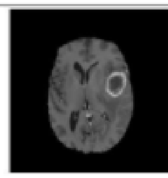
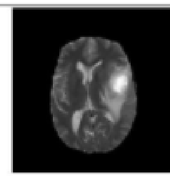
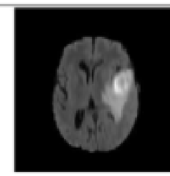
Introduction

Medical imaging analysis has been commonly involved in basic medical research and clinical treatment, e.g. computer-aided diagnosis, medical record data management, medical robots and image-based applications. Medical image analysis provides useful guidance for medical professionals to understand diseases and investigate clinical challenges in order to improve health-care quality. Among various tasks in medical image analysis, brain tumor segmentation has attracted much attention in the research community, which has been continuously studied, in spite of tireless efforts of researchers, as a key challenge, accurate brain tumor segmentation still remains to be solved, due to various challenges such as location uncertainty, morphological uncertainty, low contrast imaging, annotation bias and data imbalance. With the promising performance made by powerful deep learning methods, a number of deep learning-based methods have been applied upon brain tumor segmentation to extract feature representations automatically and achieve accurate and stable performance.

Glioma is one of the most primary brain tumors that stems from glial cells. World Health Organization (WHO) reports that glioma can be graded into four different levels based on microscopic images and tumor behavior

Grades I and II are Low-Grade-Gliomas (LGGs) which are close to benign with slow-growing pace. Grade III and IV are High-Grade-Gliomas (HGGs) which are cancerous and aggressive. Magnetic Resonance Imaging (MRI) is one of the most common imaging methods used before and after surgery, aiming at providing fundamental information for the treatment plan. Image segmentation plays an active role in gliomas diagnosis and treatment. For example, an accurate glioma segmentation mask may help surgery planning, postoperative observations and improve the survival rate. To quantify the outcome of image segmentation, we define the task of brain tumor segmentation as follows: Given an image from one or multiple image modality (e.g. multiple MRI sequences), the system aims to automatically segment the tumor area from the normal tissues and to classify each voxel or pixel of the input data into a pre-set sub-region category. Finally, the system returns the segmentation map of the corresponding input.

Table 1. Glioma images produced by different MRI sequences

Imaging Sequence	T1	T1 contrast enhanced	T2	FLAIR
Main Purpose	Distinguish healthy tissue from the tumour	Identify tumour border by adding gadolinium (Gd) contrast agent	Highlights the edema region	Shows signal of water to set apart the edema area from the cerebrospinal fluid (CSF)
Example glioma image				

Recently deep learning techniques have dominated medical image analysis and is the newest method to be used in automated segmentation. Abd-Ellah et al. [5], conclude that deep learning neural networks perform more accurately compared to traditional automated approaches. The benefit of this method, in particular Convolutional Neural Networks (CNN), is that the network can automatically learn the features needed for the task at hand, in this case for segmentation. There have thus been numerous applications of CNN for brain tumor segmentation such as [6] and also other diseases such as lung disease [7]. In other traditional machine learning approaches, feature extraction has to be explicitly determined and chosen beforehand, which leads to less accurate results

Methods

This study presented a thorough survey of techniques used in brain tumor segmentation and classification. The survey encompasses several traditional machine learning and deep learning-based methods with their quantitative performance. The conventional image segmentation techniques, that is, region growing and unsupervised machine learning used in brain tumor segmentation are presented in Table 3. The region growing with all other conventional image processing segmentation techniques is the earliest approach applied in brain tumor segmentation [161]. It is mainly affected by noises, poor image quality, and initial seed point. To overcome these challenges, an automatic seed point selection by optimization techniques and artificial intelligence-based seed point selection has been proposed [162]. In addition, it has a limitation in segmenting tumors that appear scattered across the brain. In the second generation segmentation techniques which are based on shallow unsupervised machine learning, such as fuzzy c-means and k-means grouping of pixels into more than one class has been achieved. However, these methods are also highly sensitive to noise. Therefore, through incorporating additional information and adaptively selecting the centroid, the segmentation performance of medical images can be improved [6]. In addition, the inherent ambiguous boundaries between normal tissues and brain tumors pose a significant challenge for conventional and clustering segmentation techniques. Therefore, to address this challenge, pixel-level classification-based segmentation techniques using traditional supervised machine learning have been proposed [70]. These methods are often accompanied by feature engineering, where the tumor descriptive pieces of information are extracted to train the model. Furthermore, the supervised machine learning segmentation output is further improved through post-processing [71,76].

Nowadays, conventional image processing and shallow machine learning-based brain tumor segmentation techniques are becoming obsolete due to the advent of deep learning-based techniques. The deep learning-based approach performs an end-to-end tumor segmentation by passing an MRI image through the pipeline of its building blocks. These models often extract tumor descriptive information automatically and avoid the need for handcrafted features. However, the need for a large dataset to train the models and the difficulty in interpreting the models hinders their usage in medical fields [163]. In terms of segmentation performance, it is evident from Table 4 and Table 5 that the deep learning-based and supervised shallow machine learning-based with post-processing has comparable performances. Asummary of the number of brain tumor segmentation techniques surveyed in this is given on Figure 1.

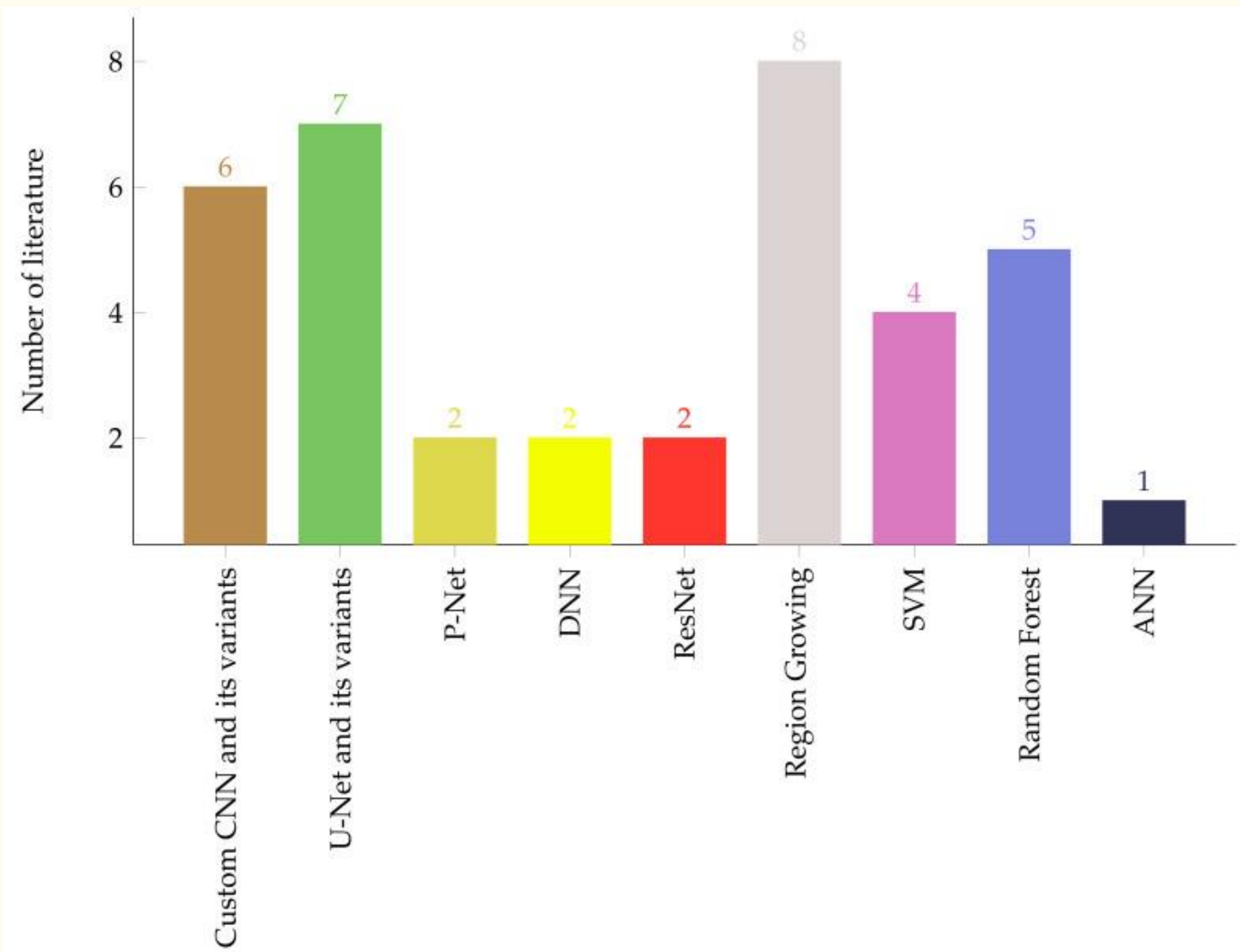


Figure 1

Number of brain tumor segmentation methods.

Aside from segmentation of brain tumor region from head MRI scan, classification of tumor into their respective histological type has great importance in diagnosis and treatment planning which actually requires biopsy procedure in today's medical practice [158]. Several methods which encompass shallow machine learning and deep learning have been proposed for brain tumor classification. The conventional shallow machine learning algorithms often consist of preprocessing, ROI detection, and feature extraction. However, due to the inherent noise sensitivity of MRI image acquisition, variations in the shape, size, location, and contrast of tumor tissue cells, extracting descriptive information is a challenging task. Therefore, nowadays, deep learning techniques are becoming the state-of-the-art approach to classify different types of brain tumors, such as astrocytoma, glioma, meningioma, and pituitary. Several brain tumor classifications have been discussed in this survey, and a summary of the number of brain tumor classification techniques surveyed in this paper are given on Figure 2.

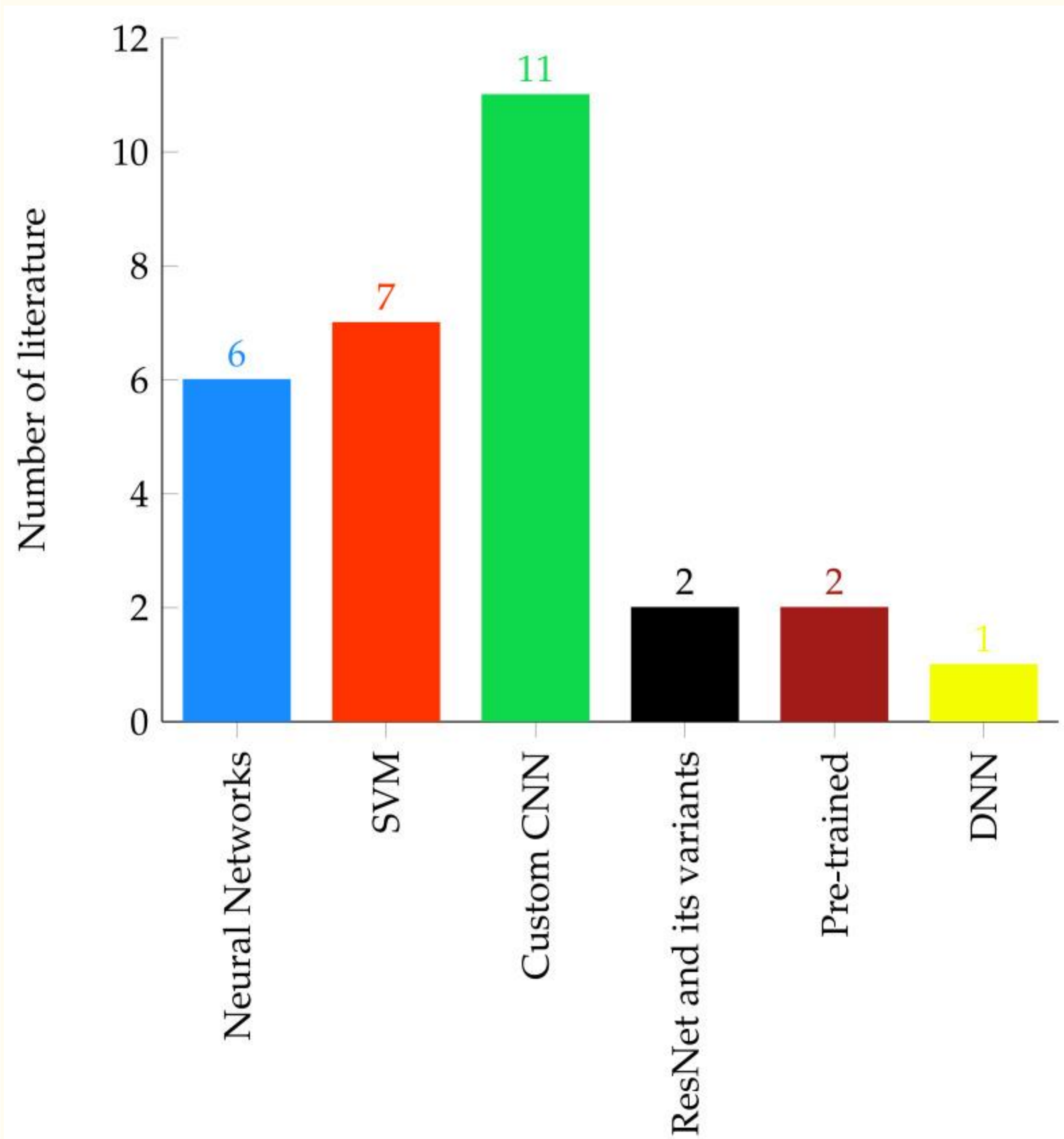


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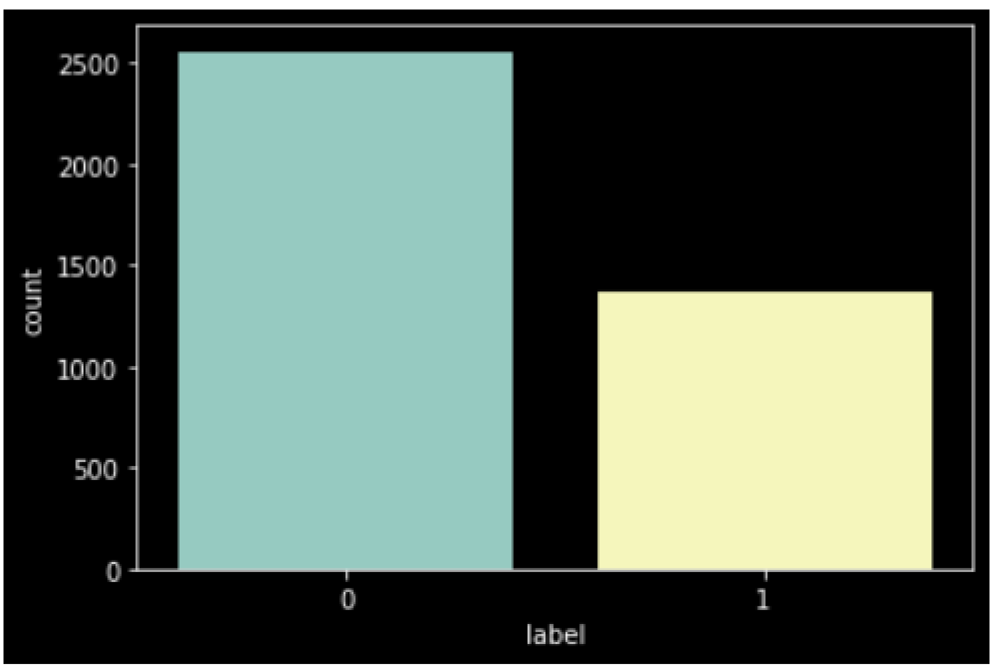
Figure 2

Number of brain tumor classification methods.

Several brain tumor datasets that are collected by researchers datasets and those that are available on repositories were used in the training and testing of brain tumor classification models. The publicly available dataset provided by J. Cheng et al. [138], which contains meningioma, glioma, and pituitary tumor in T1-WC MRI-images is one of the most commonly used datasets in the training and testing classifier models. Using this dataset, Gumaei, A. et al. [125] has achieved a classification accuracy of 94.23% using a regularized extreme learning machine, while the Kokkalla, S. et al. [153] have reported a classification accuracy of 99.69% using custom modified deep-dense inception residual network (DDIRNet). These results indicate that the deep learning-based model outweighs the shallow machine learning-based techniques for this particular dataset.

Result

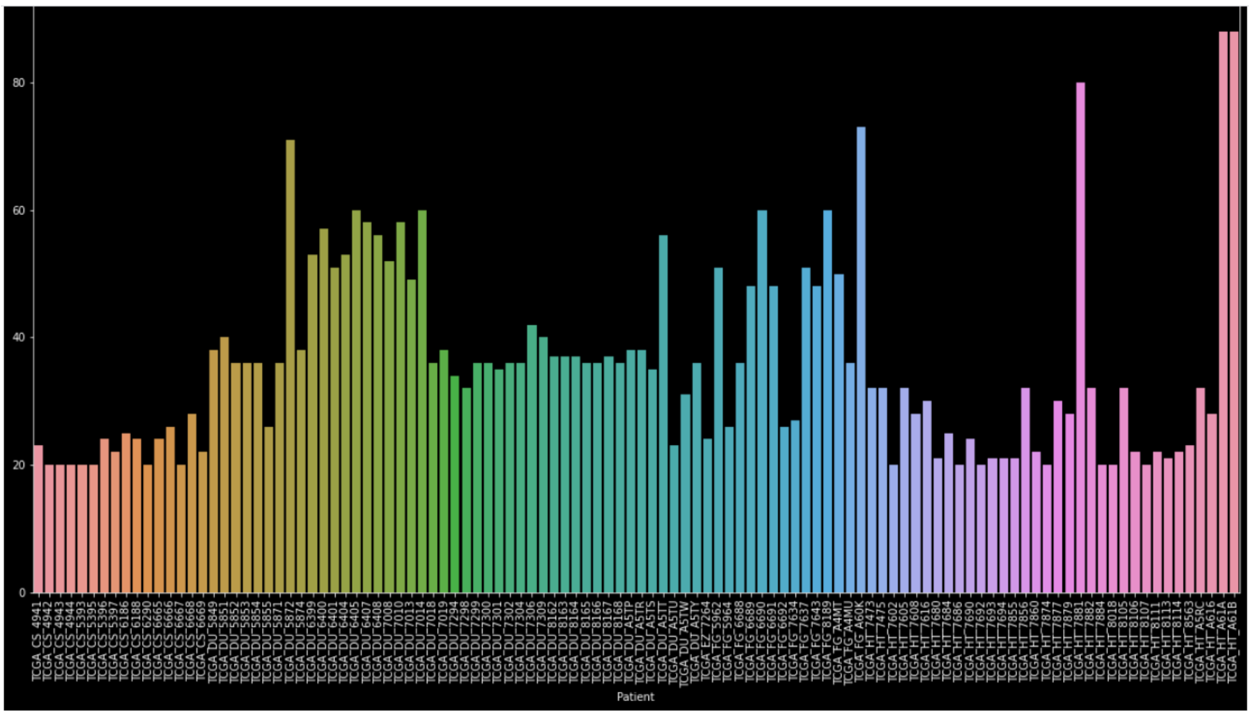



```
def path(x):
  y=x.split("/")[-1]
  z=y.split(".")[0]
  z1=z.split("_")
  return "_".join(z1[:-2])
```

```
df['Patient']=df.img.apply(path)
```

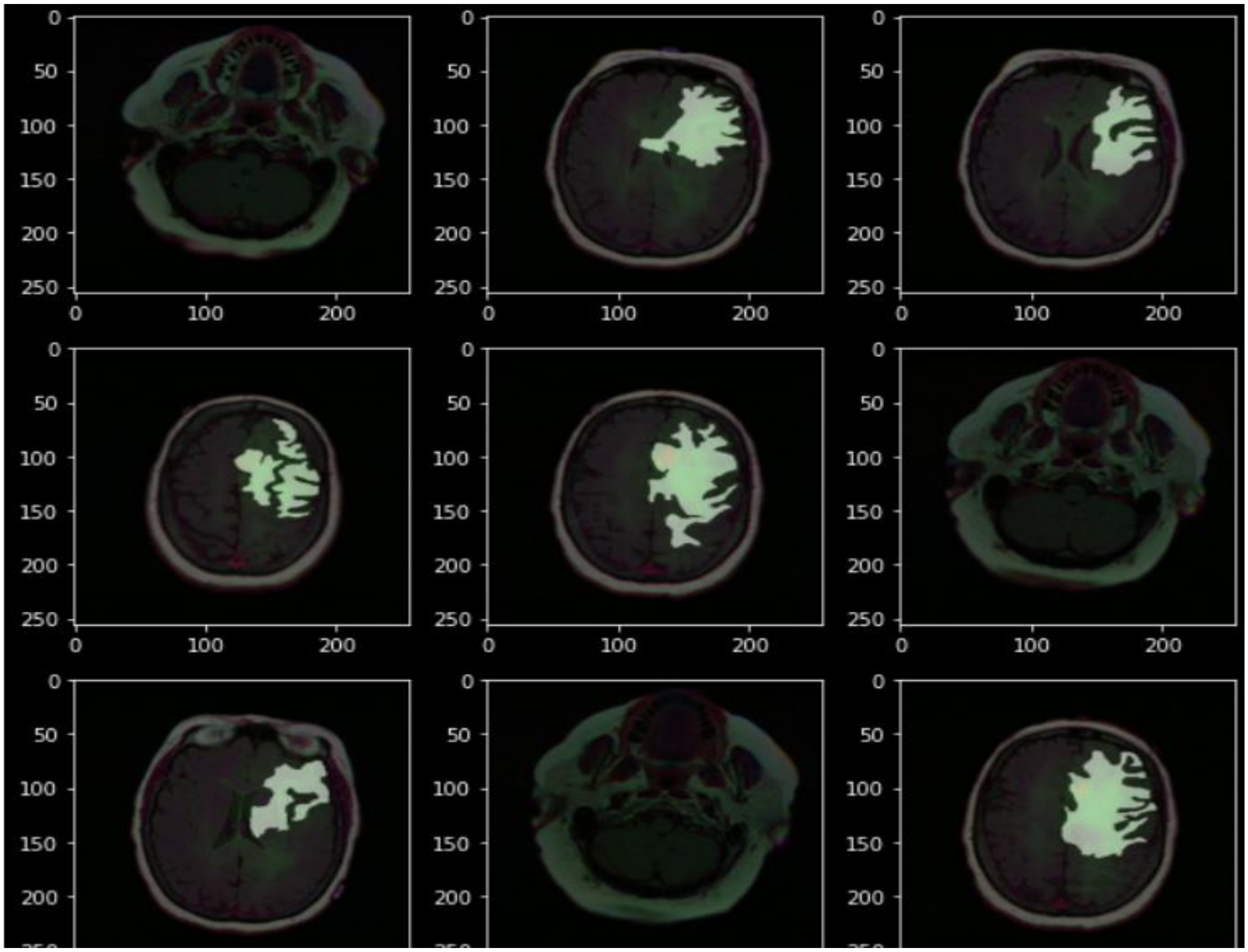
In [10]:

```
linkcode
k=df.groupby(df.Patient)
l=k.size()
plt.figure(figsize=(20,10))
plt.xticks(rotation=90)
sns.barplot(x=l.index,y=l.values)
plt.show()
```




```
rows,cols=5,5
l=k.get_group('TCGA_CS_4941')
fig=plt.figure(figsize=(16,16))
plt.title('TCGA_CS_4941')
for i in range(1,l.shape[0]):
    fig.add_subplot(rows,cols,i)
    img=cv2.imread(l['img'].iloc[i], cv2.IMREAD_UNCHANGED)
    msk_path=l['mask'].iloc[i]
    img=img/255
    msk=cv2.imread(msk_path)
    plt.imshow(img)
    #plt.imshow(msk,alpha=0.5)
```

```
plt.show()
```



Conclusion:

Image segmentation of brain tumours is still an area of active research because of its significance in image based diagnosis and remains challenging due to the variability in patients. Segmenting in 3D is an especially challenging and difficult task