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Brain Tumor Segmentation Using Volumetric Image Data

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Abstract

The number of patients infected with brain tumours rises annually. Inappropriate cell proliferation leads to tumour development. Brain tumours, while mostly malignant, can also be benign (cancerous). It is also possible to classify them as either primary or secondary. Primary tumours develop in the brain and metastasize throughout the body, while secondary tumours have their roots in other organs. The degree of abnormalities in the brain tissue is used to assign one of four grades to the tumours. The standard procedure for diagnosing a brain tumour involves a medical professional looking at MRI scans and making a decision. Obtaining satisfactory accuracy takes time and knowledge from several different individuals. Recently In the field of image classification, deep neural networks have recently become increasingly popular. However, the vast majority of studies on brain tumour segmentation have only used 2D images. A volumetric analysis of MRI scans is crucial for the rapid detection of brain tumours. A brain tumour segmentation utilising U net architecture is the focus of this study. The model examines the Brats dataset, which is available to the public, to draw conclusions about 3D photographs. The findings demonstrate the model's high level of performance.

1. Introduction

The brain is an essential organ for human control and decision making. This part of the brain is the nerve centre, therefore keeping it safe is essential. Brain tumours are the most prevalent type of malignant tumour. Except for meningioma and pituitary cancer, all other malignancies are not brain tumours. The thin walls of the brain are a common site for the development of meningiomas, a type of benign brain tumour. The death toll from brain tumours is among the highest of all diseases[1]. For effective prevention and treatment, it is essential to have a thorough understanding of the brain tumor's development. Radiologists use MRI to check for cancers in the brain. Whether or not the brain is healthy is determined by the results of this test. However, it can identify the type of tumour present in the event of an aberration[2]. The processing of MR images has become crucial for the rapid and precise identification of brain tumours because to machine learning. Figure 1 shows that the tumour areas are swamped by active tumorous tissue.

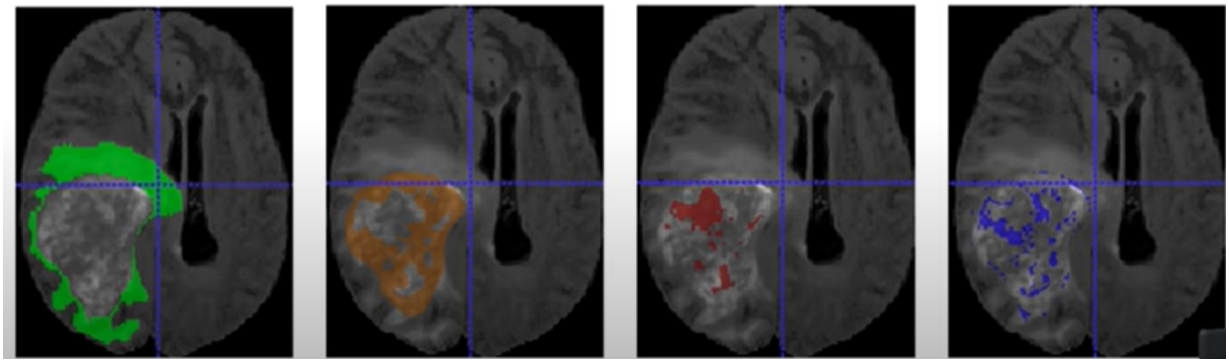

Fig 1: Different tumor tissues

- Edema: Collection of fluid or water.
- Necrosis: Accumulation of dead cells.
- Enhancing tumor: Indicate breakdown of blood brain barrier
- Non-enhancing tumor: Region in regions that are neither of the above-mentioned classes

Numerous imaging techniques have been developed to aid in the study of the brain. This section introduces the various imaging modalities available for the diagnosis of brain tumours, with a focus on magnetic resonance imaging (MRI). It is possible to group structural and functional imaging of the brain into a single category[3]. Anatomical and structural methods can be used to represent the many parts of the brain. Common neuroimaging techniques include computed tomography (CT) and magnetic resonance imaging (MRI).

The initial three parts of the method were MR image pre-processing, feature synthesis, and data extraction and classification. The median filter was used in the pre-processing phase to improve image quality while shielding the image's edges [4]. Photo features can be extracted using various clustering techniques such as k-means, fuzzy C-means, and so on. Dividing photos into smaller pieces is essential for doing so. There are a plethora of applications for this technology in brain imaging, including cellular demarcation, surgical planning, and matching. In [5], a CNN is used to segment a 3D MR image of a brain tumour. According to [6], brain anatomy may be automatically detected by a deep neural network. It is used in a voting system for a group of visual styles, such as an ensemble of intensity and adaptive form modes, where discrete Gaussian and higher order patterns, like Markov-Gibbs random field classification, are used together. An efficient and reliable deep auto-encoder has been built automatically using Bayesian fuzzy clustering [7]. Segmentation of brain tumours is performed using non-local mean filtering and Bayesian fuzzy clustering in this research. For the SVM classifier, 2D MRI images are split into left and right halves, and then statistical features including mean, homogeneity, absolute value, and inertia are calculated. More significant information is typically extracted in a second step using techniques like principal component analysis (PCA), SIFT detectors, and SURF descriptors [8].

Brain tumours are a particularly difficult case of this problem. Tumors, it turns out, come in a variety of shapes, sizes, colours, and intensities, some of which are shared with healthy tissue. Due to the varying sizes and shapes of tumours, it is impossible to use this information in diagnosis. As invasive entities, tumours are notorious for having

porous borders. Different from traditional methods, region-based approaches take on the segmentation problem from a new angle. The goal is to separate the voxels containing the object from the surrounding image so that they can be identified and deleted. Initial attempts to cluster similar voxels using fuzzy clustering failed miserably. Most contemporary region-based tumour segmentation methods use supervised statistical pattern classification techniques. The classification score is used to categorise the voids. This study aims to provide a deep learning-based framework for volumetric analysis of MRI images, specifically for the purpose of segmenting brain tumours

Literature Review

Super pixels were used by Sakshi Ahuja et al.[9] to detect brain tumours and segment the brain, respectively. VGG 19 transfer learning was used to train this model on the BRATS 2019 brain tumour segmentation challenge dataset. The tumour was divided into LGG and HGG images using the superpixel technique. As a result, the average dice index was 0.934, which was significantly lower than the actual data. U-Net was used by Hajar Cherguif et al.[10] to segment medical images based on their semantic content. U-Net architecture was used to create a good 2D segmentation network. A dataset from BRATS 2017 was used to test and evaluate the model. Dice coef of 0.81, 27 convolutional layers, 4 deconvolutional layers comprised the proposed U-Net architecture.

A Convolutional Neural Network (CNN) model was used by Chirodip Lodh Choudhury et al. [11] to get accurate results from MRI scans using deep learning techniques. In addition, a fully Connected Neural Network (FCN) was proposed as a third layer of a CNN architecture. It was possible to achieve an F-score of 97.33 and an accuracy rate of 96.05 per cent. Semi-automatic segmentation of MRI T1 weighted images using an active contour model was used to investigate the possibility of a brain tumour. Researchers in [12] examined the performance of three different morphological active contours: a snake active contour, and a geometrical morphological active contour. According to the data, MGAC performed the best of the three.

Concatenation was used for the deep learning model by Neelum et al.,[13], who investigated the possibility of a brain tumour. Brain tumours can be detected and classified using the deep learning models Inception v3 and DenseNet201. As part of the tumour classification, the Inception v3 model was pre-trained on how to extract the features. Then, a softmax classifier was used to classify the data. Hybrid Classifiers were utilised by Ms. Swati Jayade et al.[14]. Tumors were divided into two categories: malignant and benign. The GLCM feature extraction method was used to create the dataset here. It was suggested that classifier efficiency be improved by combining KNN and SVM methods.

SVM (Support Vector Machine) was used by Zheshu Jia and colleagues[15] to carry out an automatic heterogeneous segmentation. A classification system known as the probabilistic neural network classification system had been used to train and check the accuracy of tumour detection in MRI images. The automated segmentation of meningiomas was the focus of this model, which made use of a multi-spectral brain dataset. An edge detection method that included Gabor transform and clustering was used by Akey Sungheetha, DR. Rajeesh Sharma R.[16]. This study made use of approximately 4500 MRI images and 3000 CT scans. Similar features were separated into sub-groups using K-means clustering. The author used Fuzzy c means to represent the images as histogram properties.

This study used a bayesian approach to classify brain tumours using capsule networks by Parnian Afshar et al.[17]. The results of tumour detection were improved by using a capsule network rather than a CNN because CNN can lose spatial information. The BayesCap framework was proposed by the group. The model was put to the test using data from a well-known database of brain tumours. In this study [18], the researcher aimed for a higher level of accuracy and did so by relying on data from two distinct sources. In the first step, various methods like LTP (Local ternary pattern), Contourlet transform, and curvelet transform are used to extract features from a given dataset. DNN, a supervised learning technique, was used for classification in the second and most important part. One thousand MRI images were used to test this hybrid method. Experiment results show that the DNN with Contourlet transform technique has a 97.5 percent accuracy rate compared to the other feature extraction methods discussed in this paper. Within the bare minimum of 0.088 seconds. The curvelet transform technique, on the other hand, yielded the same results but required 0.15 seconds of computation, compared to the previous method's 0.02 seconds. However, LTP (Local ternary pattern) is only accurate to 18.33 percent of the time. Other performance evaluation parameters, such as error rate, sensitivity, and f-measure, were also calculated. The DNN and contourlet transform combination was found to be the most effective in all tests.

A significant effort by the researcher [19] that expresses the experimental results in terms of time and accuracy. The algorithm's performance can be demonstrated using these parameters. In the end, this study compares the performance of various algorithms, such as DNN, ANN, and KNN. The accuracy percentages shown by the experiments and statistical analysis are 93.18 percent, 90.90 percent, and 81.81 percent, respectively. According to the results, it is clear that DNN outperformed the other two remaining methods, KNN and ANN, in terms of accuracy. To conduct the experiment, MRI images were used, but the most important point is that the DNN-based fusion technique yielded better results and a higher degree of accuracy.

1. Implementation And Results

Figure 3.1 depicts the proposed methodology. This study makes use of the BRATS 2020 image dataset. 3D MRI scans of a brain tumour form the basis of this data set. Enhancing images with pre-processing techniques improves their quality and allows for more accurate analysis. Following this, a machine learning model is developed on Unet, which is then tested and validated through training and testing. The following sections go into detail about each of these steps.

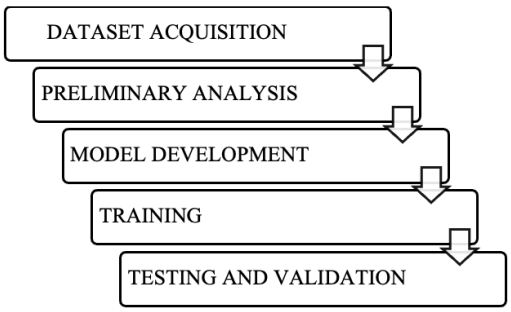

Fig 3.1: Proposed Methodology

3.1 Database Description

The BRATS 2020 brain tumour dataset is used for 3D MRI image segmentation. BRATS is a multicentric dataset of skull-stripped MR sequences that is freely available to the public. Various hospitals contributed their data, which was then resampled to a 1 mm3 isotropic resolution. Gliomas of various grades are represented in the dataset through MR images. Sagittal, coronal, and axial images in the dataset have dimensions of 240*240*155. Four sequences (FLAIR, T1 weighted, T2 weighted, T1 post contrast) and a pixel level segmentation mask for each patient are included.

1.2 Preliminary analysis

The BRATS dataset consists of MRI images and a subsequent label for a variety of patients using three different modalities. An image is a four-dimensional object in that it is comprised of the first three dimensions (MRI modalities) and a fourth dimension (the label).The next step is to extract label information from the training images.. Figure3.2 shows the labels and training images in different planes, such as the front, side, and top planes. In order to ensure the validity of training data, this step isn't necessary, but it is essential

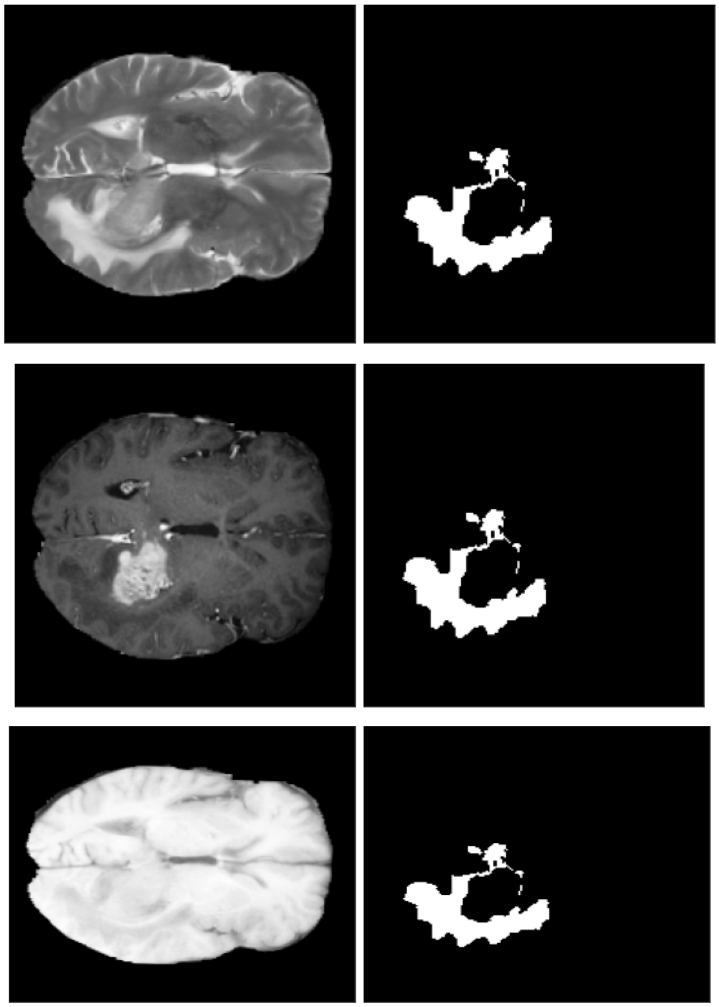

Fig 3 .2: Extracted tumour patches from different modalities (T1-w, T1w-post contrast and T2w)

In contrast to classification, segmentation necessitates the extraction of high pixel-level information from the images. Another way of putting it: Segmentation is the process of classifying images on the basis of individual pixels, with each pixel being assigned to either tumour tissue or healthy tissue. 190,190,50 patches or 3D volume shapes are used for each label and training image in this work. This is a necessary step to reduce the amount of time it takes. Step 3: Train large data sets with segmentation training. The extracted patches are subjected to standardisation and minmax scaling. A json file is used to store the weights that have been collected.

4.1 Model Development

U Net architecture is used in the present research. Biomedical images were first processed using UNet, a convolutional neural network that evolved from the traditional convolutional neural network. Biomedical convolutional neural networks require us to distinguish not only whether a patient has a disease, but also where the abnormality is located. As a general convolutional neural network, the input image and the output label are the same. It's shaped like a "U" in the middle. There are two major parts to the architecture: a contracting path on the left, made up of the general convolutional process, and an expansive path, made up of transposed 2d convolutional layers on the right. The details are as follows:

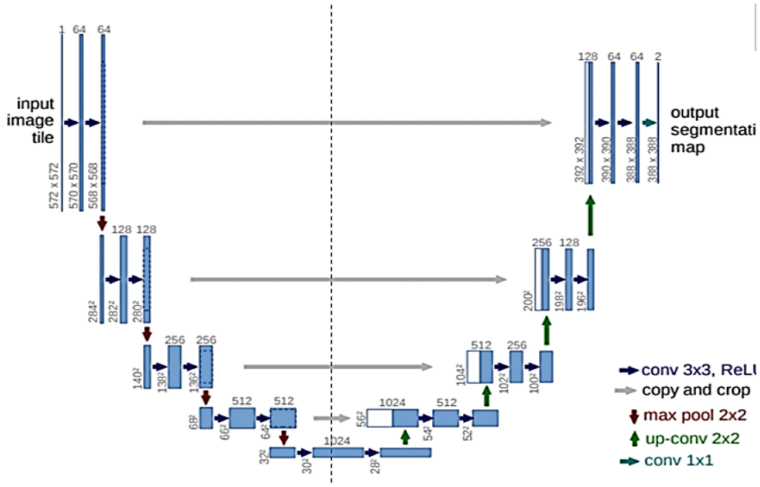

Figure 3.3: Proposed model

4. RESULTS

Dice loss/score and Intersection over unit are the two most important metrics for assessing the performance of transfer learning models..

$$L_{Dice} = 2 * \frac{\sum_i x_{actual} x_{predicted}}{\sum_i x_{actual} + \sum_i x_{predicted}}$$

Intersection over Union (IoU) In the context of segmentation evaluation, Intersection over Union (IoU) is a common criterion. We take into account the target matrix's varying pixel ratio in creating our resultant matrix. As part of the Dice calculation, this metric is also used.

$$IoU = \frac{x_{actual} \cap x_{predicted}}{x_{actual} \cup x_{predicted}}$$

When evaluating medical image segmentation, Dice coefficient (DSC) is widely used. Between 0 and 1, it is a measure of the overlap between the segmentation and the actual data.. The better the dice score, the better the segmentation. Statistical methods such as sensitivity analysis and specificity testing are also frequently employed. True positives, another term for sensitivity, refers to the percentage of positive results that were predicted correctly. This is the percentage of negative outcomes that are accurately predicted. To put it another way, specificity refers to the percentage of normal tissue regions in the ground truth. In the real world, however, sensitivity indicates the location of the tumour. On the basis of BRATS 2020's training, validation, and testing sets, the performance of our proposed architecture is evaluated. Using this method, the Dice coefficient is 0.83. In Fig. 4.4, the dice losses in training and validation are clearly shown.

Fig.4.5 shows the Intersection over Union results in training and validation. The final IoU result was a 0.6. The IoU is an important performance metric, but previous research has not examined this aspect.Transfer learning improves the U net's multimodal segmentation performance, as demonstrated in this study. We used pre-trained encoders and decoders from the VGG family for this approach. Table 4.2 provides a comparison of our findings to those of other researchers. Superior results can be achieved by utilising more cutting-edge strategies.

Table 4.1 Results

SNO	PARAMETERS	VALUE
1	Dice Loss	0.82
2	IoU Score	0.67
3	Sensitivity	0.89
4	Specificity	0.1

Table 4.2: Performance Comparison

Ref	Type of analysis	Architecture	Dice loss (Whole tumour)
[18]	2D	CNN	0.79
PROPOSED	3D	VGG	**0.83**

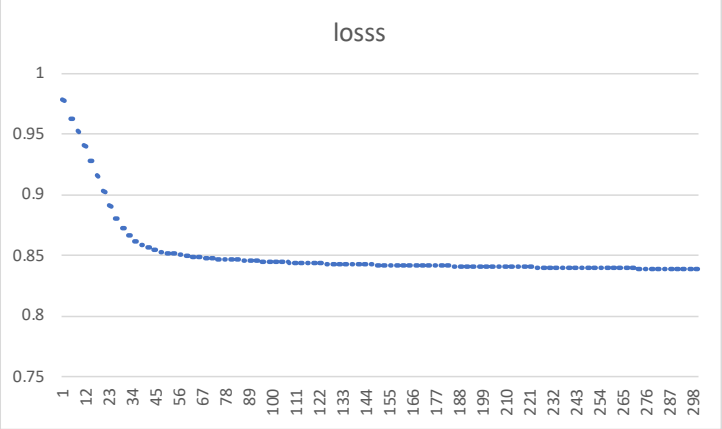

Figure 4.4 : Dice loss

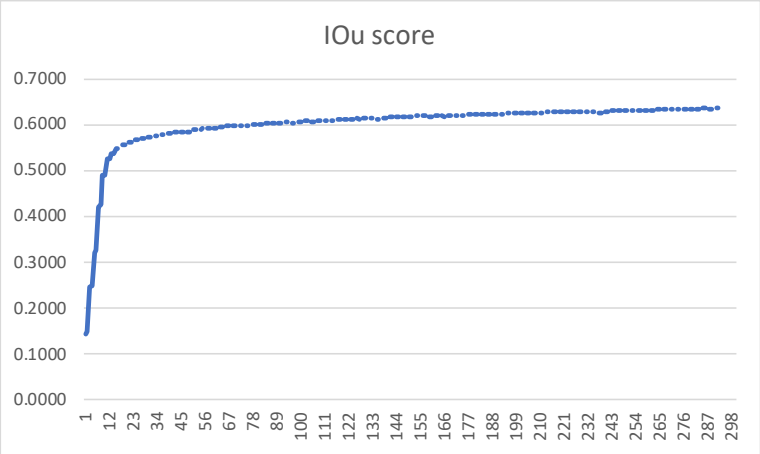

Figure 4.5 : IOU score

4 Conclusion and Future work

The mortality rate for brain tumors is among the highest of any illness category. It is crucial and perhaps lifesaving to detect cancerous tissues at an early stage. Manual observation takes more time and produces less accurate results. Using deep learning and computer vision, a fully automated method for detecting and separating brain tumors from healthy tissue can be created. This study aims to create a deep learning model capable of processing volumetric MRI scans in three dimensions to distinguish between tumor and healthy tissue. Because different types of brain tumors are recognized in different detection modalities and planes, 3D image analysis is particularly relevant in the context of brain tumours. In this study, we employ a U-net architecture. The Brats 2020 dataset is used to verify the suggested model. The experimental outcomes show the effectiveness of the proposed method.

To get around the high computational need and training time, transfer learning may be added to the planned research in the future. The term "transfer learning" is used to describe models that have already been trained. Recent studies can be expanded to include a categorization step.

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