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COMPUTER SCIENCE AND ENGINEERING

Mini Project

BRAIN TUMO SEGMENTATION

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1. ABSTRACT

Brain tumour segmentation aims to separate healthy tissue from the tumorous regions present in the tumorous areas. This is a necessary step in diagnosis & treatment planning to maximize the likelihood of successful treatment. Resonance imaging provides detailed information about brain tumour anatomy, making it a crucial tool for effective diagnosis, which is requisite to replace the prevailing manual detection system where patients believe the skills & expertise of a person. As a solution to this, a brain tumour segmentation detection system is proposed where experiments are tested on the collected BraTs 2020 dataset. This dataset contains four different MRI modalities for every patient as T1, T2, T1ce, and Flair, and as an outcome, a segmented image & ground truth of tumour segmentation, i.e., class label, is provided. An utterly automatic methodology to handle the task of segmentation of gliomas in pre-operative MRI scans is developed using a U-Net-based DL model. the first step is to rework input image data, which is further processed through various techniques—subset division, narrow object region, category brain slicing, watershed algorithm, & feature scaling was done. All these steps are implied be- for entering data into the U-Net DL model. The U-Net DL model is utilized to perform pixel label segmentation on the segment tumour region. The algorithm reached high-performance accuracy on the BraTs 2020 training, validation, as well as testing dataset. The proposed model achieved an IoU of 0.72.

Keywords: brain tumour segmentation; deep learning; U-Net; BraTs 2020; MRI

2. INTRODUCTION

A brain tumour is defined as a cancerous or noncancerous mass or development of abnormal cells within the brain. Gliomas are categorized into High-Grade Glioma (HGG) and Low-Grade Glioma (LGG), based on the pathological assessment of the tumour. Brain tumour segmentation aims to separate healthy tissue from tumorous regions. This is a vital step in analysis & treatment progressing to improve the likelihood of effective treatment. Nowadays, biological science has emerged with several extended research problems under the category of Digital Image Processing (DIP). The detection of the tumour & its classification, detection of the cancerous region and its classification, testing, and inspecting crucial parts of the human body are a few applications that fall under this category. Out of varied medical science problems, automatic brain tumour segmentation & detection is of utmost importance, and efforts are being made so as to

effectively handle this problem. For clinical diagnosis, appropriate classification and segmentation of medical images are necessary. Therefore, several algorithms and methods have been presented for manual, semi- & fully automated tumour segmentation due to the complicated tumour segmentation process in the MRI image. Then, manual segmentation is performed by a radiologist, which is considered the gold standard. However, expert segmentation is not very precise & is subject to inter-observer variability. Expert segmentation is time-consuming as it involves visualizing spatial and temporal profiles and therefore examining many enhanced datasets & pixel profiles while determining the injury boundary. Then the best solution offered by computer vision is to employ fully automated systems using machine learning techniques.

In the proposed work, the tumour region in the MRI scan is segmented using a U-Net based DL model, which has a fully connected Convolutional Neural Network (CNN) foundation. A few image processing methods like narrow object region filter together with subset division, category brain slicing, & feature scaling are incorporated before inputting the processed image to the DL model. Research work is completed in the same direction & a few pre-filters & have feature scaling are employed to urge the improved dice coefficient; the result section demonstrates success in getting high accuracy in tumour segmentation.

The main contributions of this project are summarized as follows:

- Explored advanced DL models in depth and proved the conjectured performance evidence of U-Net DL models for brain tumour image segmentation for detection.

- Experimented segmentation with standard U-Net, further explored and incorporated subset division, category brain slicing, feature scaling, & narrow object region filtering prior to feeding to U-Net model and examined the performance enhancement of U-Net architecture by incorporating all these pre-learning processes.

- Specifically examined a few challenging unsuccessful tumour segmentation test cases & observe an important parameter tuning for result refinement.

- The manuscript presented a state-of-the-art brain tumour detection technique that, in combination with a few image processing processes, followed by a deep learning model, can provide accurate brain tumor segmentation. Undoubtedly, this approach can assist in the medical workflow as well as give clinical direction in identification, therapy planning, & later evaluations.

3. Material and Research Flow

The studied literature broadens the understanding of the principal practices used to get the best performance and efficiency. Based on the reviewed literature, the brain tumour

MRI scan dataset was taken for practical consideration, and a research flow was designed to achieve the research objective.

A. Material

The MICCAI BraTS 2020 dataset was acquired from the **Kaggle**. The data provided is part of BraTS 2020. The BraTS dataset contains brain images of patients in every four modalities and the segmented results for each patient. The different modalities are—Native (T1), T2-weighted (T2), post-contrast T1-weighted (T1ce), and T2 Flair Attenuated Inversion Recovery (FLAIR). Corresponding to each record, a tumour-segmented region and ground truth of tumour segmentation (OT) are provided in the BraTS 2020 dataset. The ground truth contains annotations of three nested subregions—Whole Tumor (WT), Tumor Core (TC), and enhancing tumour (ET). Two more datasets for testing and validation are provided along with that. The multimodal scans in the BraTS dataset are available as NIfTI files (.nii.gz). The OT (ground truth of tumour segmentation/segmented result) is analyzed for comparison with our predicted output. All the imaging datasets were segmented manually, and their annotations were affirmed by experienced neuroradiologists.

BraTS 2020 Dataset details:

Input Image Size:	128*128*155
Training Dataset:	275 Images
Validation Dataset:	69 Images

B. Research Flow

This section lists the details of the research flow of the work done to realize the most effective accuracy for brain tumour detection using MRI scans. The research flow was designed to extract tumour segmented regions as compared to classification. The input images were taken from the well-known BraTs 2020 dataset. Broadly, this research work was performed in two steps-(1) pre-learning process techniques & (2) a deep-learning model for tumour image segmentation. Under pre-learning, the method started with informational transformation, which converted the tumour image dataset into a machine-readable python format. The subset division step was done to divide the dataset because the formed dataset is enormous in size and has resource restrictions. Furthermore, category brain slicing & narrow object regions downsized the images by removing unnecessary content from the input image. Basic level image segmentation was accomplished by a watershed algorithm, and finally, feature scaling was applied to standardize the independent features, which ended the pre-learning process.

For biomedical imaging research problems, image localization is a specialized & essential task that needs an adequate deep learning mode. Therefore, U-Net architecture is the most preferable model for localization within the image out of variants of conventional convolutional neural network models. U-Net architecture aims to pinpoint the localized region of brain tumours. The strength of U-Net architecture is to identify unclear and irregular discontinuities & limits to a good extent, which was otherwise posing a good challenge, especially against edge-based methods for tumour region detection research problems. The last need of the research is to determine the performance of the research methodology, that which dice coefficient & loss function has been validated for the achieved outcome of DL-based segmentation. This performance measure is applicable to quantify the performance of the segmented tumour region.

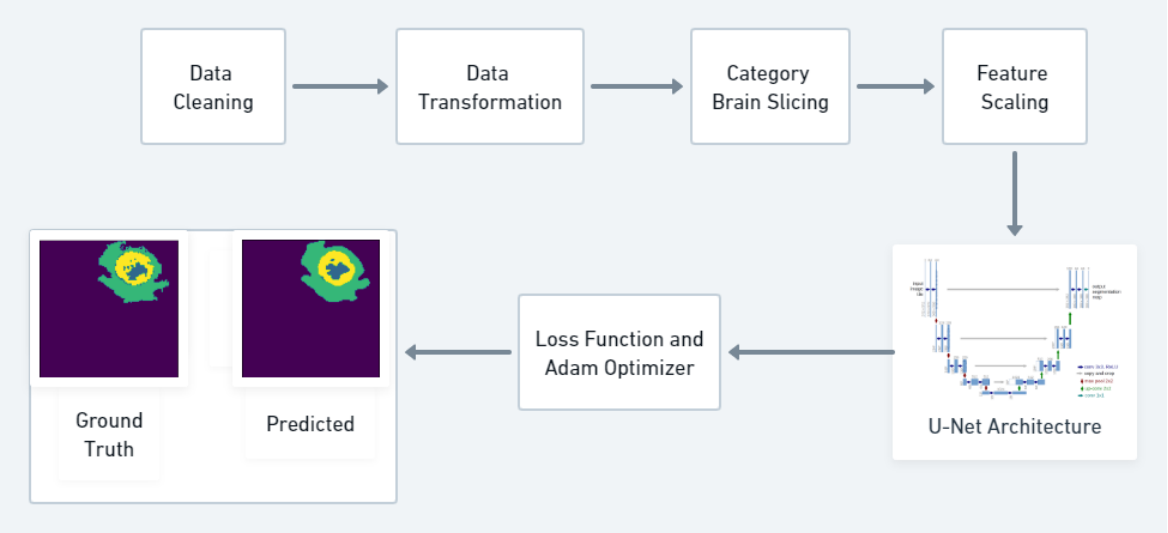


Figure: Deep learning-based tumour detection architecture.

4. Methodology

A. Pre-Learning Process Techniques

a. Data Transformation

As mentioned in the data above, the multimodal scans in the BraTS 2020 dataset were formatted in NIfTI files (.nii.gz). All the given images were processed to convert from the .nii.gz format to NumPy arrays. This was done using a scaler(MinMaxScaler, fit_transform) and then combined all t1ce, t2, flair images, and mask MRI images is also converted in NumPy array containing four layers in the tumour. Each patient's MRI scan volumes were collected and directly combined to form a NumPy array. The developed NumPy array is of size (X,128,128,155), where X: number of

data (BraTS 2020 contains 275 patients' scans under Training Data Set and 69 patients scan under Validation Data Set.

b. Category Brain Slicing

All the 2D slices corresponding to each MRI 3D volume image would not show the tumour region. Therefore, the slices which can contain the tumour region were grouped to get better accuracy. This implementation of brain slicing can be automated by learning features or set manually by excluding a few first & end slices. Thus, from the 155 slices that corresponded to each MRI 3D volume imager, i.e., from the 13th slice to the 141st slice.

c. Feature Scaling

Feature Scaling is a technique used to standardize independent features provided in the information onto a specified interval. It is a requisite part for tumour detection through the deep-learning process because the learning model uses gradient descent, which converges faster with scaled features as compared to without it. Z-score normalization was applied, which transforms each feature value range from zero to its unit-variance. Z-Score was computed using Equation (1), as given below. $Z - Score = x - \mu\ \sigma$ (1) where Z is the Z-transformation value of the specific feature value x, μ is the mean, & σ is the standard deviation of the image features

B. Deep Learning Model for Tumor Region Segmentation

Biomedical image processing needs specialized deep learning techniques due to localization requirements to realize the optimal outcome. For this problem, localization aims to pinpoint the position of the tumour regions while locating, for example, attempts to assign a class label to each pixel. Standardized convolution neural networks don't seem to be apt for biomedical image segmentation problems as these models are used for classification tasks to assign each image a corresponding class label instead of identifying the segmented region. The identical U-Net model was used as a deep learning methodology based on fully convolutional neural networks. The significant idea is to supplement a usual contracting network by successive layers, where up-sampling operators replace pooling operators. Hence, these layers increase the resolution of the output. High-resolution features from the contracting path are combined with the up-sampled output to localise. A successive convolution layer can then learn to assemble a more precise output supported by this information. In the up-sampling part, we also have an enormous number of feature channels, which permit the network to propagate context information to higher resolution layers. As a consequence, the expansive path is more or less symmetric to the

contracting path and yields a u-shaped architecture. The figure also illustrates the network architecture, within which each box corresponds to a multi-channel feature map. It consists of a contracting path on the left side & an expansive path on the proper side. The contracting path follows the typical architecture of a convolutional network. It consists of the repeated application of two 3 × 3 x 3 convolutions (unpadded convolutions), each followed by a rectified linear unit (ReLU) and a 2 × 2 x 2 max pooling operation with stride three for downsampling

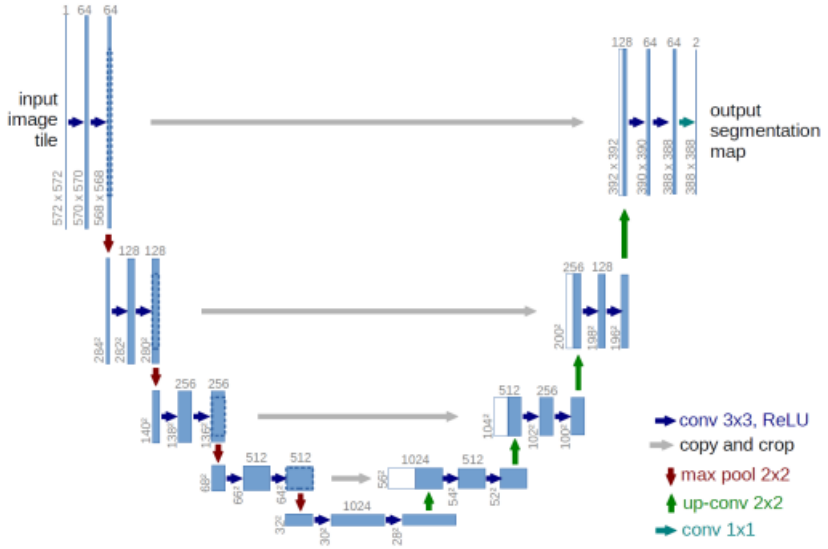


Figure: U-Net architecture (example for 32 × 32 pixels in the lowest resolution)

In our work, at each downsampling step, the numbers of feature channels are doubled. Every step in the expansive path consists of an upsampling of the feature map followed by a 2 × 2 x 2 convolution that halves the number of feature channels, a concatenation with the correspondingly cropped feature map from the contracting path, and two 3 × 3 x 3 convolutions, each followed by a ReLU. The cropping is necessary due to the loss of border pixels in every convolution. At the final layer, a 1 × 1 x 1 convolution is used to map each 16-component feature vector to the desired number of classes. Hence, the U-Net Convolutional networks comprise of two parts:

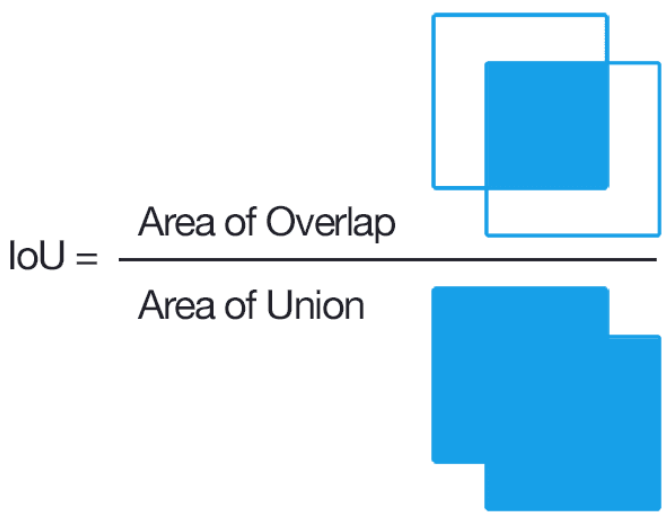
• A contracting path similar to an encoder to capture the context from a compact feature representation.

• Asymmetric expanding path is similar to a decoder, which allows for accurate localization. This step is done to retain boundary information (spatial information) despite downsampling and max-pooling performed in the encoder stage.

5. Experimental Setup and Results

MRI tumour identification was performed using the deep learning-based segmentation

model U-Net in this work. IoU Score and loss functions were defined to validate the performance of the experimented approach-predicted segmented brain tumour region. Several python libraries were used to implement the process and validate the implementation. Some libraries/packages used are Pip package, OpenCV, Glob, Numpy-1.14.1, Random, Scaler, Keras, TensorFlow, Matplotlib, Segmentation Model-3D etc. Performance Evaluation Measures Performance evaluations were used to measure the learning model efficiency on the training and test set for the supervised learning prediction. The output of the U-net deep learning-based detection model was an image that depicts the localized tumour. The comparison in the output image with the original growth truth image was computed to define the difference between the original and predicted tumour region. The IoU Score was considered more intuitive to measure the output effectiveness of the image segmentation problem. It was used to compute the percentage of overlap between the two images' ranges, from 0 to 1. An IoU Score equivalent to 1 denotes perfect and complete overlap. Usually, the IoU Score has been used in existing medical imaging problems to evaluate the model. Hence, the IoU score was used to quantify image segmentation performance. IoU Score is an evaluation measure to know the similarity of the objects. It is defined as the size of the overlap of the two segmentations divided by the total length of the two objects, i.e., the score for a particular class is the size of the overlap between the predicted region and its authentic counterpart. The IoU score determines the amount of spatial overlap between the ground truth segmentation and the predicted segmentation. The formula to obtain the IoU Score is defined as



In medical volumes, it is common that the anatomy of interest is present in only a very small space in the scan. In the task of brain tumour segmentation, the tumour is present in a very compact area. This results in the training procedure getting caught in the local minima of the loss function and causes the predictions to be strongly biased towards the background. Consequently, the foreground region is only partially detected or, in some cases, even missing. Several previous approaches used loss functions, which use sample

re-weighting wherein the background area is provided less importance than the foreground area at the time of training.

6. Result

U-Net Deep Learning Model Outcome for Brain Tumor Detection In addition, to analysing the best performing deep learning model, we also monitored how the model performance is gradually improved with epochs for training and validation datasets. The model was then tested on random test images and the output was compared to the Ground Truth. To quantify the performance of our image segmentation, an IoU Score was used. The proposed methodology, where the U-Net deep learning model is used after applying pre-learning techniques, was able to produce a competent outcome. The IoU Score outcome of the proposed approach on training, validation, and test set is tabulated in Table 6. After training the network with the U-Net model accuracy is 0.9916 and loss(Dice Loss + Focal Loss) is 0.7862, the Mean IoU Score of Validation Dataset in 0.72.

7. CONCLUSION

A challenging problem of pixel label segmentation of brain tumors using MRI data, which is required for brain tumor diagnostic procedures, was tackled in the present work. The proposed model initially used diverse image processing steps to upgrade the brain image and images provided in sub-regions in a well-defined manner. Undoubtedly, accurate segmentation of a brain tumor into its sub-regions provides a deeper insight into the condition of the tumor. Hence, in the proposed work, image data transformation, image slicing for the refined region (category brain slicing, subset division, and narrow object region), initial level image segmentation (watershed algorithm), and feature scaling were experimented with before inputting in the deep learning model. The U-Net deep learning model was used to localize the tumor region; the contracting part of U-Net captures the context from the compact feature representation and expansion path and performs accurate localization. Parameter tuning of contracting and expansion path layers in a symmetric manner was applied in order to achieve high accuracy. High IoU Scores, accuracy, and speed of this network allow for large-scale application in brain tumor segmentation. This method can be implemented in the clinical workflow for reliable tumour segmentation and for providing clinical guidance in diagnosis, surgical planning, and follow-up assessments. Although improvement and future research directions are opened in this as well, some are as follows:

• Developing a reliable system with an easy-to-use user interface for the proposed model. The interface would allow doctors to upload an image and get results on the

location of the tumour and its class.

• The model can be enhanced to predict the survivability of patients suffering from a brain tumour.

• Explore a more robust system for the vast database of clinical images, which could be noisy, be affected by external factors, and have reduced quality.

• Implement the model for the discovery and segmentation of tumours in different parts of the body.