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BRAIN TUMOR SEGMENTATION USING DL

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ABSTRACT:

Magnetic Resonance Imaging (MRI) is the most commonly used non-intrusive technique for medical image acquisition. Brain tumor segmentation is the process of algorithmically identifying tumors in brain MRI scans. Apart from providing real-time segmentation of MRI scans, the proposed architecture does not need large amount of data to train the proposed lightweight U-Net. Moreover,no additional data augmentation step is required. The lightweight U-Net shows very promising results on BITE dataset and it achieves a mean intersection-over-union (IoU) of 89% while outperforming the standard benchmark algorithms. Additionally, this work demonstrates an effective use of the three perspective planes, instead of the original three-dimensional volumetric images, for simplified brain tumor segmentation.

INTRODUCTION:

Tumors are groups of cells which form abnormal tissue or growths within the human anatomy. Tumors can either be malignant where the growth is cancerous and will invade surrounding cells, or benign where the suspected growth is not cancerous[1] . Manual identification of these abnormal growths in human anatomy is notonly onerous but might also be difficult from the perspective of a medical physician. Hence, the need for intelligent systems which can automatically detect the presence of cancer in a desired region of the human body ,. With the advancement of technologies in the medical field, there has been a tremendous impact on diagnostics and predictive analysis of diseases [2]. We observe an advancement of healthcare analysis in brain tumor segmentation, heart disease prediction, stroke prediction,, identifying stroke indicators , real-time electrocardiogram (ECG) anomaly detection , and amongst others[3].

Brain tumors are such abnormal growths found within the human cranium. Given the complex and sensitive nature of the brain, a non-invasive technology, i.e. Magnetic Resonance Imaging (MRI), is the most popular pick for brain tumor diagnosis. These images are three-dimensional scans of a patients brain and can be visualized on either of its three respecting image planes (Coronal, Sagittal and Transversal), as shown in Fig. 1 . Each perspective plane displays its information regarding a potential abnormal growth within the cranium. This classification of MRI scans based on the perspective planes has been noted to improve the analytical results while detecting brain tumors[4] .

Brain tumor segmentation aims to autonomously and accurately identify the size and location of a brain tumor from MRI scans. While traditional machine learning techniques require hand crafted features to perform well, most of the current research is focused on using deep learning networks to segment a region of interest (ROI) from an input image [5]. Although considerable success has been achieved using deep learning, they eitherrequire large amounts of annotated data or they depend on aggressive data augmentation techniques . However,a lightweight approach is almost always preferred for practical implementations To this end, this paper1 makes the following key contributions:

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The paper demonstrates an effective use of the three perspective planes, instead of the original three-

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dimensional volumetric images, for simplified brain tumor segmentation

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A lightweight implementation of U-Net is proposed to provide accurate real-time segmentation

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The proposed model is systematically benchmarked with several widely used segmentation algorithms.
BRAIN TUMOR SEGMENTATION TECHNIQUES:

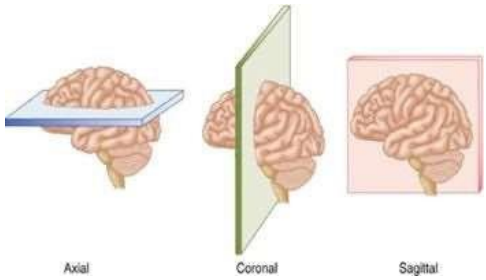

Image segmentation is a crucial area of research in the broad domains of image processing and computer vision, with applications in varied fields [6]. The challenge is to classify each pixel as a part of different objects inthe image. Over the years, many algorithms have been proposed for this task . The process of segmentation hasseen widespread use in the field of medical imaging as well. Particularly for MRI scans, most of the previousstudies modifies the existing techniques of image segmentation to manipulate the three-dimensional volumetric images [7]. These modified networks are further fine tuned to improve the performance over the given task.

Based on the complexity of the algorithm they use to extract the ROI from input images, segmentation techniques can be classified into 4 broad categories [8]. In the subsequent sub-sections, we will explain these categories and some of the corresponding algorithms that fall in each category [9].

THRESHOLDING

Thresholding is a very simplistic segmentation technique that is used to convert a gray-scaled or a red–green–blue (RGB) image into a binary image. Although this technique is simplistic in nature, it is very effective in extracting the ROI from an image [10]. Prior research on this particular segmentation technique explores the useof Otsu's method and global thresholding for medical image segmentation. Otsu's method is a popular segmentation algorithm used in the area of pattern recognition where features of an ROI are extracted from an image for further processing [11].

However, more recent success in this domain was obtained using simple binary thresholding coupled with the watershed algorithm to segment brain tumors from MRI brain scans . The proposed method first uses median filtering to remove various noise levels that may be damaging the quality of each image. Binary thresholding is then applied to the image, followed by the watershed algorithm to extract the ROI from the brain scan. Finally, small batches of morphological operations are used to refine the segmentation which results in a more accurate segmentation [12].

CLASSIFIERS

Classifiers are common techniques used in segmentation which share a similar approach with methods used in supervised learning algorithms that are used in several applications These algorithms learn features, whichare critical to make the classification decision, from an existing dataset of annotated (or labeled) images. These labels are manually tagged to create the ground truth for learning [13]. A simple classification algorithm which iscommonly used for image segmentation is the k-nearest neighbor classifier. In this machine learning algorithm, features of each pixel are computed at first [14]. Then the pixels with high degree of similarity within these features,are merged together [15].

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Hidden Markov Models (HMM) have been proven to perform significantly better than Support Vector Regression (SVR) models when used for brain tumor segmentation. Particular research has focused this topic on how HMM can produce a better Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE) . The research applies a HMM to a two-dimensional MRI scan, extracted from the BITE dataset The designed model will segment the cancerous portion of the image and produce a set of probabilities which will belong to eitherof the categories, i.e. cancerous/non-cancerous [16]. These images were further classified using sorting factor-kappa, and their segmentation performance was evaluated based on the chosen evaluation criteria.

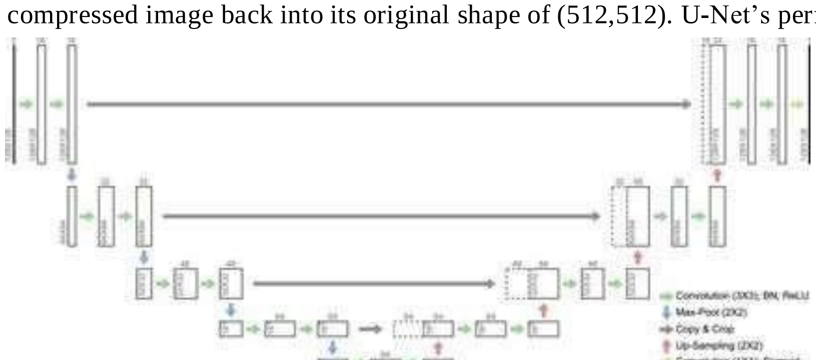
METHODOLOGY:

METHOD

U-Net is a fully connected CNN used for efficient semantic segmentation of images. Such U-Net deep neural network fits in various analytical tasks of wide ranging application. This is particularly useful where the input data is the form of images. This architecture has several applications ranging from consumer videos earth observations and medical imaging The U-Net architecture is based on an autoencoder network where the network will copy its inputs to its outputs an autoencoder network functions by compressing the input image into a latent-space representation which is simply a compressed representation of the images indicating which data points are closest together. The compressed data is later reconstructed to produce an output. An autoencoder network contains two paths, an encoder and a decoder. The encoder compresses the data into a latent-space representation while the decoder is used for the reconstruction of the input data from its latent-space representation. U-Net uses a convolutional autoencoder architecture where the convolutional layers are used to encode and decode the input images.

Similarly, to an autoencoder network, U-Net contains two paths, a contraction path (encoder) and a symmetric expanding path (decoder). The encoder path of U-Net captures the context of the input image, this path is simply a pipeline of convolutional and pooling layers. The decoder path uses transposed convolutions enabling precise localization. There is no fully connected feedforward layer (or dense layer) in the U-Net, and it only contains the stacks of convolutional layers and max-pooling layers. Although U-Net was originally designed for 572 × 572 images, it can be easily modified to work with any image dimension . Several stacked convolutional layers can enable the network to learn more precise features from the compressed input images, see Fig. 4 .

U-Net operates on the assumption that the input image and the corresponding binary map are equal in image dimensions. In other words, if the input image is of shape (512,512), the corresponding binary mask must match this shape. The input image is compressed to fit into a latent-space representation. The decoder will reconstruct this compressed image back into its original shape of (512,512). U-Net's performance



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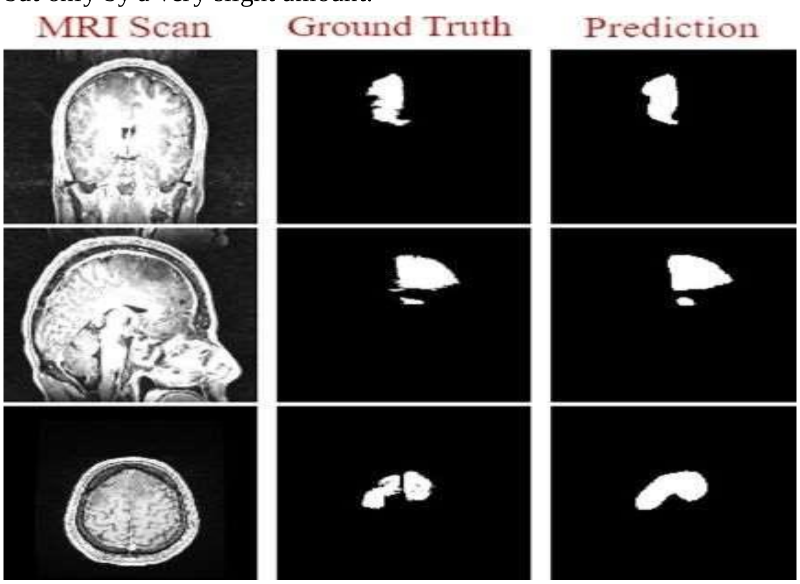
RESULTS:

SUBJECTIVE EVALUATION

Training the network began in small iterations where we monitored the segmentation performance based on iterations alone. Early results using 10 epochs produced poor results across two of the image planes notably the sagittal and coronal planes. Poor segmentation results were expected based on the small epoch range used during training, however, adequate results were recorded on the transversal plane. This is likely due to the size of each dataset as the transversal dataset had the most images as the patient's tumor is most prominent from this particular perspective. To further improve these results we increased the networks epoch range to 50 and monitored the results to see if the segmentation performance had improved. Using 50 epochs significantly improved the networks segmentation performance across all three perspective planes. Fig. 5 shows the results across all three perspectives using only 50 epochs and the proposed network architecture from . Here, model 1 (or first model) is the standard U-Net architecture, whereas the model 2 (or the final model) is the proposed U-Net with optimized filter values.

To further improve the networks segmentation performance we began undertaking small experiments using the entire dataset of images. This dataset contains all images extracted from all three perspective planes. The purpose of this study is to experiment on U-Nets ability to extract features from images from different perspectives. Running the network using this new dataset for 50 epochs only produced very promising results. Increasing the number of epochs to an extreme size does increase the networks overall segmentation accuracy but only by a very slight amount.



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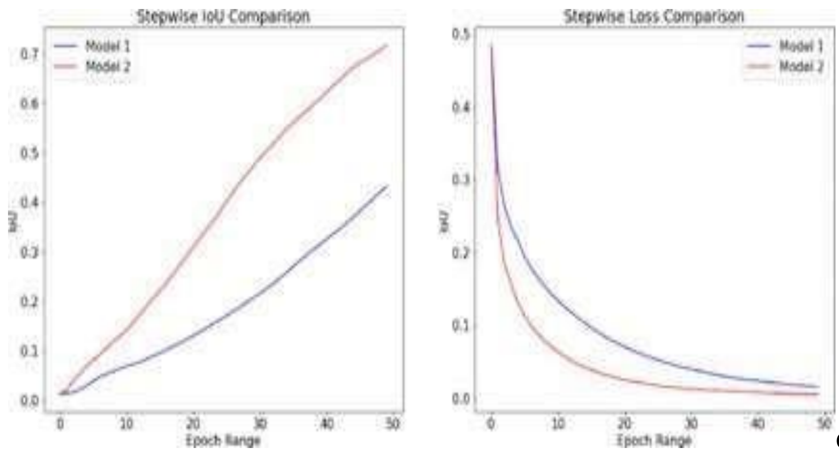

COMPARISON OF PROPOSED METHOD WITH OTHER METHODS:

Several algorithms were chosen to benchmark to further evaluate the segmentation performance obtained using U-Net. These algorithms specified in Section 2 of the paper were chosen based on their success on biomedical image segmentation. Each algorithm was used to compare our segmentation results obtained using our proposed model. Each algorithm was tested using the extracted test sets of each of the four available datasets. Fig. 8 shows the three ground truth images which correspond directly to the predictions generated in Fig. 9.

Comparing the results obtained using U-Net to those obtained to benchmark, we observed that our proposed model outperformed each of these benchmarking algorithms. While the deep learning methods perform segmentation task automatically, the other three benchmarking algorithms (Thresholding, K-Means, Fuzzy C-Means) needed more 'manual' interference. They perform better when the tumor is clearly distinguishable at the pixel level in terms of intensity and isolation. This also means that to achieve maximum performance when the parameters are fine-tuned separately for each image, which essentially renders the whole process useless. The three-manual segmentation algorithms were implemented for automatic segmentation of brain tumors from MRI images

CONCLUSION:

Due to the purpose of our study, we have seen how U-Net an existing deep learning architecture for biomedical image segmentation can be altered and fine-tuned for brain tumor segmentation

Our implementation of U-Net is lightweight and can perform accurate segmentation's, without the need for aggressive data augmentation. This proposed network could be used in a medical setting for trained physicians to have a second evaluator to a patients MR image. Research on the particular topic of brain tumor segmentation has advanced rapidly with the application of deep learning, however, more studies are needed to further improve the performance of a proposed network as the ratio between the predicted images False Negatives and False Positives is crucial in biomedical image analysis.

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