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Report: Deep Learning in Image Segmentation

A Novel Deep Learning Method for Localization and Segmentation of Brain Tumours from MR Images

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Abstract

Magnetic Resonance Imaging (MRI) segmentation involves dividing an image into regions to isolate areas of interest. This is useful in medical imaging, particularly in segmenting T1-weighted contrast-enhanced MRI (CE-MRI) images. The process involves two steps: localization of tumour regions of interest in the MR Images, and contouring to define the boundaries of these tumour regions. To automate this process, a Deep Convolutional Neural Network (CNN) can be used. CNNs can learn complex patterns in image data, enhancing the precision and efficiency of MRI segmentation. This makes it a valuable tool in medical imaging analysis.

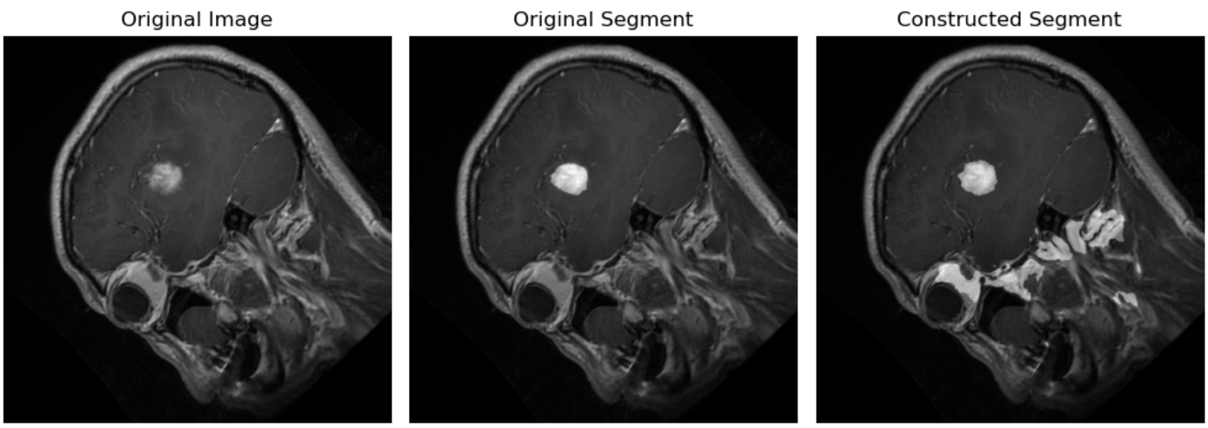

Figure 1: Output generated after training: (a) Original MR image, (b) Superimposition of original mask on corresponding MR image (c) Superimposition of predicted mask on corresponding original MR image

1 Introduction

Brain tumor segmentation is the process of outlining and detecting the boundaries of tumors in brain pictures obtained by medical imaging techniques like MRI. The purpose is to separate the tumorous region from healthy brain tissue.

- CNN-based networks have high computational cost.
- When dealing with high-resolution MRI scans, the processing cost increases dramatically.
- Traditional object recognition algorithms often employ bounding boxes to define objects of interest.
- In a simple CNN-based model, this may be accomplished by first utilizing a CNN and then adding a fully linked layer.
- However, fixed-length completely connected layers are ineffective when the number of items to be recognized varies (like in brain tumor segmentation).
- Become challenging when number of object detection is not fixed.
- The proposed research introduced Automated deep learning technique for brain tumor segmentation using a

CNN and a modified U-Net.

2 Related work

BraTS Challenge:

- Since 2012, the University of Pennsylvania's Perelman School of Medicine has been hosting the BraTS challenge.
- Brain tumor segmentation utilizing medical imaging data is its main area of interest.
- The competition seeks to develop cutting-edge methods and algorithms as well as automate the identification of brain tumors.

3 Dataset

- Dataset comprises 3064 T1-weighted contrast-enhanced files in .mat format.
- Each file contains:
  - **Label**: 1 for meningioma, 2 for glioma, 3 for pituitary tumor.
  - **PID**: Patient ID.
  - **Image**: Image data of size 512 × 512.
  - **TumorMask**: Binary image representing the tumor region.

4 Preprocessing

- Resize each MR image without distortion to dimensions of 256 × 256.
- Apply Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance the tumor region.
- CLAHE aims to eliminate noisy elements and enhance visible trainable features.

5 Methods and Approaches

1. **Preprocessing and Resizing**:
   * Preprocess MRI images: reduce noise, normalize intensity, strip skull.
   * Resize images to 256 $\times$ 256: maintain consistency for analysis.
   * Use a dataset with 3064 T1-weighted slices: each with tumor labels.
2. **Region-Based CNN for Tumor Localization**:
   * Employ CNN to identify tumor areas based on local features.
   * Each identified region represents a potential tumor area.
3. **ROI Classification**:
   * Use separate CNN to classify each region as tumor or normal.
   * Output probability scores indicating tumor presence.
4. **Boundary Box Localization**:
   * Define bounding boxes around potential tumor areas.
   * Enclose tumor boundaries within the original MRI image.
5. **Modified U-Net for Precise Segmentation**:
   * Utilize modified U-Net for accurate tumor segmentation.
   * Train on boundary box area for precise segmentation.
6. **Final Tumor Segmentation**:
   * Generate pixel-wise segmentation mask using trained U-Net.
   * Extract segmented tumor region from original MRI.
7. **Postprocessing and Visualization**:
   * Remove artifacts, smooth segmentation mask.
   * Enhance visualization for accurate tumor region.

6 Proposed Architecture

1. Implement a custom CNN architecture specifically designed for accurate brain tumor segmentation.
2. Input to the network is the pre-processed image from Section 3.1.
3. Incorporate attention mechanisms, including channel attention and spatial attention, which are crucial for image processing tasks.
4. Adopt a 2D U-Net architecture as the basis, known for its effectiveness in biomedical image segmentation.
5. Integrate channel and spatial attention within the network to improve segmentation accuracy.
6. The proposed attention module includes both channel and spatial attention mechanisms, operating in parallel with a skip connection.
7. Utilize skip connections to reduce redundancy and sparsity within the architecture.
8. Refer to Figure 2 for a visual representation of the detailed architecture.

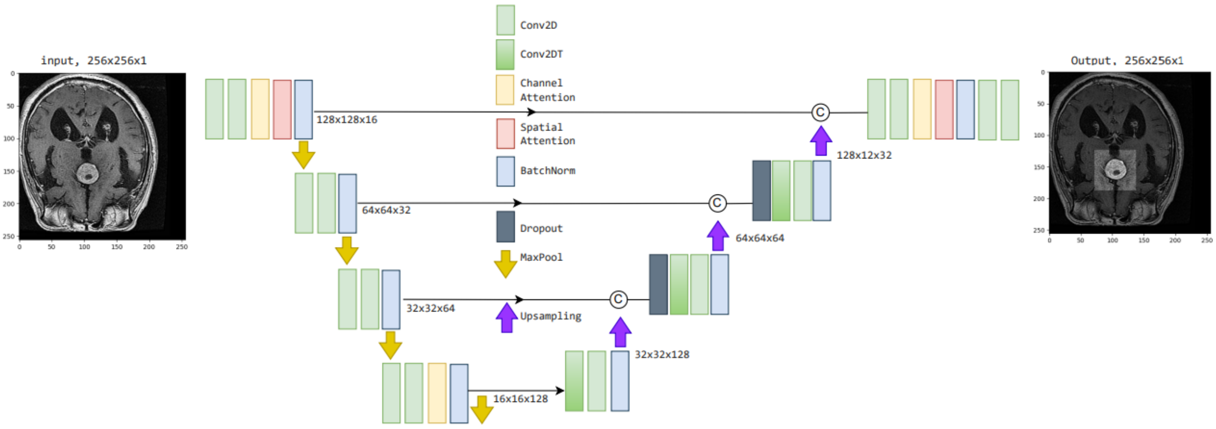

Figure 2: Visual Representation of the Proposed Architecture

7 Training Steps of Network

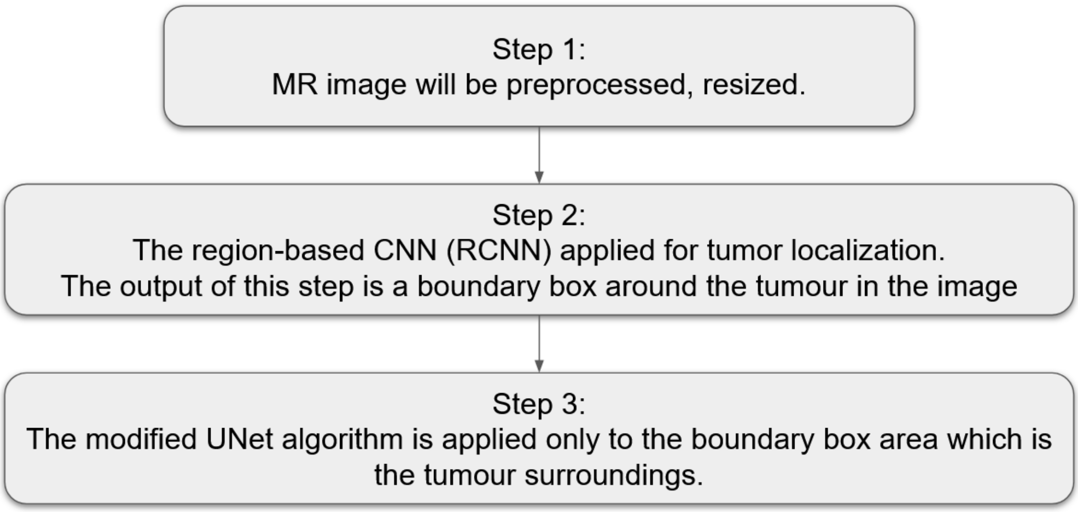

Figure 3: Flow diagram of Training Network

8 Experiments

1. Trained model for 2 epochs and ploted predicted tumor mask can be seen in figure 4. The model has already started given good results.

2. Trained model for 10 epochs and ploted predicted tumor mask can be seen in figure 4. The model predictions has improved drastically.

3. Trained model for 100 epochs and ploted predicted tumor mask can be seen in figure 4. The model prediction has reached almost equal to original masks.

9 Results

- Dice coefficient: 0.8995

- My Dice coefficient: 0.744

- Outperformed previous methods in brain tumor segmentation using MRI images

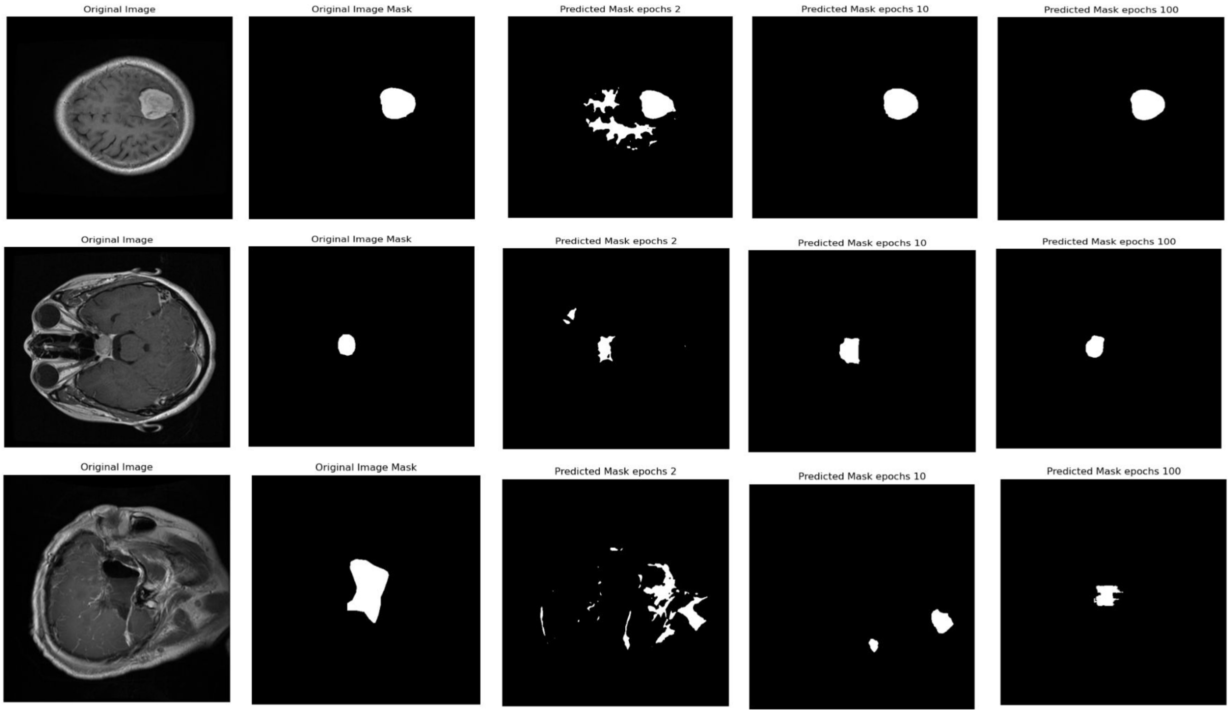

Figure 4: Results predicted by model after traning from 2, 10 and 100 epochs. (a) Original input MR image, (b) Original input tumor mask, (c) Predicted tumor mask after 2 epochs, (d) Predicted tumor mask after 10 epochs, (d) Predicted tumor mask after 100 epochs. It can be seen that as epochs increases the correctness of predicted tumor mask increases.

10 Conclusion

- The proposed method takes less computation time.
- In fewer epochs gives good results.
- Has good performance as compared to the previous method.

References

[1] Jun Cheng. Brain tumor dataset 3064 t1-weighted contrast-inhanced images. *School of Biomedical Engineering.*

[2] Thomas Fevens Somayeh Davar. A novel deep learning method for localization and segmentation of brain tumours from mr images. 2024.