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Deep Learning for Brain MRI Segmentation

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Abstract— Brain magnetic resonance imaging (MRI) plays a central role in this setting, providing detailed anatomical information for clinical evaluation. Segmentation of her MRI images of the brain is an essential step to obtaining meaningful information for diagnostic and therapeutic purposes. Deep learning, especially convolutional neural networks (CNN), has emerged as a powerful solution to automate brain MRI segmentation and improve accuracy. In particular, convolutional neural networks have demonstrated remarkable performance in segmenting brain structures such as gray matter, white matter, and cerebrospinal fluid, as well as detecting abnormalities such as tumors and lesions. The purpose of this article is to provide an overview of current deep learning-based segmentation approaches for quantitative brain MRI. First, we review current deeplearning architectures used to segment anatomical brain structures and lesions. Next, we summarize and discuss the performance, speed, and characteristics of deep learning approaches. Finally, it critically assesses the current situation and points out possible future developments and trends.

Keywords—Deep Learning, Convolutional Neural Networks, Brain MRI.

I. INTRODUCTION

Magnetic Resonance Imaging (MRI) is a non-invasive medical imaging technique used to visualize the internal structures of the body in detail. MRI uses a strong magnetic field and radio waves to generate images of the body's organs, tissues, and other structures. Unlike X-rays and CT scans, MRI does not use ionizing radiation, making it a safer option for imaging in many cases. Among all the modalities MRI is most popular as it provides images with high contrast for soft tissues. Brain MRI plays a vital role in diagnosing various brain disorders like schizophrenia, cancer, Alzheimer’s disease, multiple sclerosis, epilepsy and many more infectious brain diseases.

Nowadays, deep learning has emerged in the field of medical imaging and is helping a lot in predicting the abnormalities. In the field of brain MRI, it helps in segmentation of the brain images into various parts such as cerebrospinal fluid, gray matter, white matter. Being a subfield of artificial intelligence, it has various algorithms like UNet, CNN etc. with remarkable accuracies to train and test the data. It involves training neural networks to learn and extract features directly from data, hence, this makes deep learning well suited for image analysis tasks. In our model we have used one of the most demanded algorithms in the brain MRI segmentation i.e., CNN.

Convolutional Neural Network (CNN) was introduced in 1989 but gained great interest after achieving amazing results in

ImageNet competition in 2012. This algorithm nearly halved the error rates of the many considered great computing algorithms. It was specially designed for processing structured grid data, particularly for tasks involving images and video analysis. CNN is basically composed of three layers: convolution, pooling and fully connected layers. Convolutional and pooling does feature extraction and the fully connected layer maps those features into a final output. In our model, the final output is mapped into two classifications: 'Tumor' and 'No Tumor' brain MRI images.

With the use of CNN, deep learning allows us to remove the need of human-engineered features and heuristics and uncover patterns and features through MRI data in an automated way. But despite of so many advantages and high accuracies, the successful implementation of model has lots of challenges, such as potential overfitting, need of large datasets and correct predictions of results. However, the current model provides the accuracy around 95-96%.

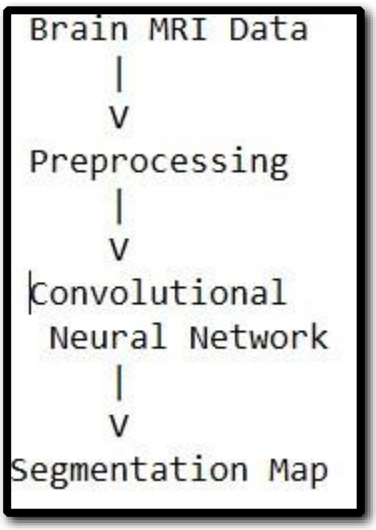

Fig1.1 Basic approach of MRI Segmentation model

II. LITERATURE REVIEW

This section will discuss about the previous works done in the field of Brain MRI Segmentation:

The first one says MRI images are to be taken from three views direction: sagittal, axial and coronal[4] for the better result predictions

In 2014, one of the review article on Brain MRI by Ivana Despotovic[1] talked about the various segmentation techniques of different accuracy and complexities and reviewed the most popular methods commonly used. They mentioned that image segmentation is performed on 2D and 3D volumetric images. However, most of the research is focused on 2D images. The 2D segmentation methods can be extended to 3D imagery segmentation but they come up with high complexities and slow response time.

The other one written by Svolos P.[2], says that the tumor imaging depend more on the experience of anatomy experts. The results obtained are subjective and the process is laborious and time-consuming. However, different people or the same person draw different conclusions at different times. So, the best way to solve this issue is to introduce the automated algorithms for the image segmentation.

Compared with traditional convolutional neural networks that only operate on one scale, Zhao and Jia [3] convolve images on different scales. However, because there is no image preprocessing before training, the variance obtained in the experiment is large, and the experimental results are not ideal. Most methods will choose to use 2D filters for feature extraction, but using 3D filters can make fuller use of image features.

Researchers may assess deep learning algorithms, gauge the relevance of discoveries, and draw conclusions about brain MRI scans with the use of statistical methods. For instance, the Dice coefficient, which measures the geographical overlap between the segmentation of the model and the actual data, aids in precisely identifying the regions. Similar to how the F1 score evaluates the model's general performance, it is a balanced measure of accuracy and recall. The receiver operating characteristic (ROC) curve's Area Under the Curve (AUC) also measures how well the model can discriminate between normal and pathological brain areas. These statistical techniques improve the accuracy and dependability.

Brain MRI segmentation is a crucial task in medical image analysis, and deep learning has made significant advancements in this field. Here are few popular deep learning algorithms used for Brain MRI segmentation:

1. U-Net:

U-Net is a widely used architecture for semantic segmentation tasks, including brain MRI segmentation. Its encoder-decoder structure allows it to capture both global and local features in the MRI images. U-Net has been adapted and extended in various ways to improve its performance, making it a standard choice for medical image segmentation.

2. DeepLab:

DeepLab is known for its excellent performance in semantic segmentation. The DeepLab architecture incorporates atrous (dilated) convolutions, which enables it to capture multi-scale information effectively. Variants like DeepLabV3+ have been used for brain MRI segmentation to achieve highly accurate results.

3. 3D CNNs:

While most deep learning models are designed for 2D image segmentation, 3D convolutional neural networks (3D CNNs) are tailored for volumetric data like 3D brain MRI scans. These models take into account the spatial relationships in all three dimensions, which is crucial for accurate brain segmentation and the detection of abnormalities.

4. ResUNet:

ResUNet combines the principles of residual networks (ResNet) and the U-Net architecture. By incorporating residual connections, it helps mitigate the vanishing gradient problem and facilitates the training of very deep neural networks. This hybrid architecture has shown promising results in brain MRI segmentation tasks.

These deep learning algorithms leverage the power of neural networks to automatically learn and extract features from brain MRI data, enabling highly accurate and efficient segmentation of anatomical structures and abnormalities within the brain. Researchers and clinicians continue to explore and adapt these algorithms to enhance their performance and clinical utility.

III. PROPOSED METHODOLOGY

An algorithm must first be trained using a data set called a training data set. Once these algorithms are trained, they can be used to perform a variety of tasks. Machine learning is used in various industries to perform various tasks. Most of the time, machine learning algorithms are used for predictive purposes or to detect hidden things.

Deep learning-based segmentation approaches for brain MRI have gained increasing interest due to their self-learning and generalization capabilities over large amounts of data. As deep learning architectures mature, they gradually improve in performance over previous state-of-the-art classical machine learning algorithms.

First, we review current deep learning architectures used for segmentation of anatomical brain structures and brain lesions. Next, we summarize and discuss the performance, speed, and characteristics of deep learning approaches. Finally, it critically assesses the current situation and points out expected future developments and trends.

This methodology outlines all the steps done to build the model:

1. Data collection and preprocessing:

The whole dataset was taken from the kaggle[5](you may download the data from the same reference) and all the target labels were done after importing all the necessary libraries. The

libraries used here are matplotlib, numpy, pandas, tensorflow, keras, PIL, sklearn.
The path to the classified image were defined and the target labels were considered as:
No Tumor as 0
Yes Tumor as 1

Then we converted image into numpy array and scaled the image array.

2. Split the Data:
The whole dataset will be divided into training, validation and testing subsets. Commonly, the 70% data goes for training, 15% for validation and 15% for testing. In our model, the dataset has been split into the same ratio.

Majority of the data goes for training to teach models how to extract features using machine learning algorithms relevant to specific goal whereas less data is used for validating predicted outputs and testing phase. The model's accuracy depends on the data used.

3. Model Design and Training
Here, we have chose to work with sequential CNN model. In this model, all the layers were added sequentially, one after the other. At first, we intialized sequential model, then we added convolutional layer with 80 filters, 3x3 kernel size and 'relu' activation.
The second step involved addition of max pooling layer with 2x2 pool size and then another convolutional and max pooling layers were added. Then the output from previous layer was flatten.
The upcoming step involved addition of fully connected layers and the output layer with the number of neurons corresponding to the number of classes in the classification task.

After the model is created, it is trained using the training dataset using loss-functions and optimization technique. The training was monitored with validation data to prevent overfitting.At last, post processing techniques were applied to refine the segmentation results.

4. Model Evaluation
The evaluation of model is done through the test dataset. In our model's case the accuracy on test data was around 0.7605. Also, we plotted the model loss in fig 3.1.

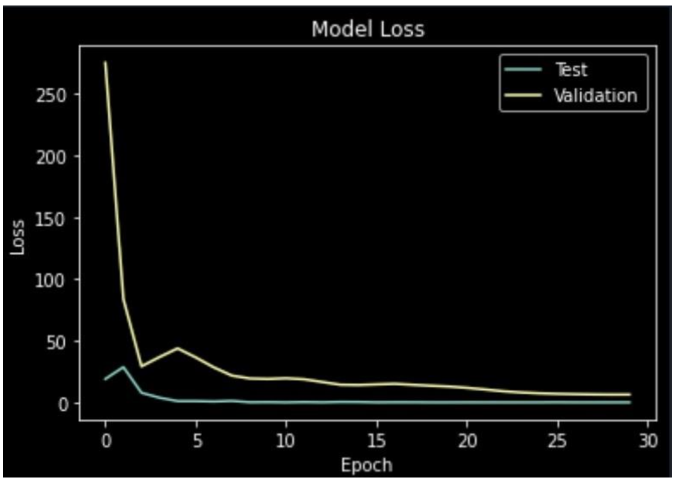

Fig 3.1 Model Loss

5. Checking the Model
On making our model go through different picture sets, it was able to classify them as tumor(fig 3.2) images with confidence of 99.97% and non tumor(3.3) images with 100% confidence.

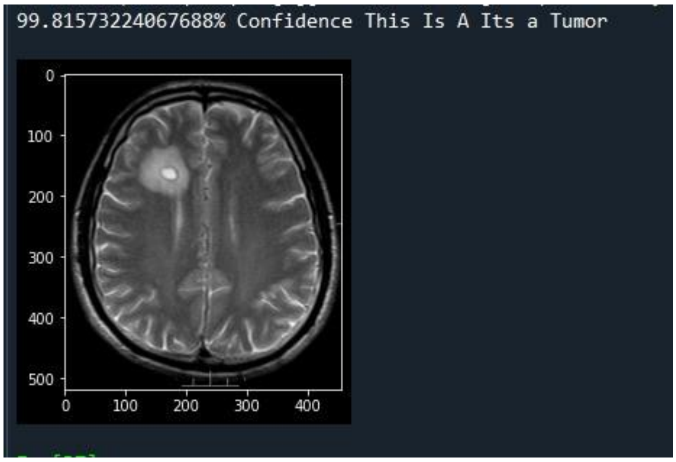

Fig 3.2 Brain Tumor- Positive

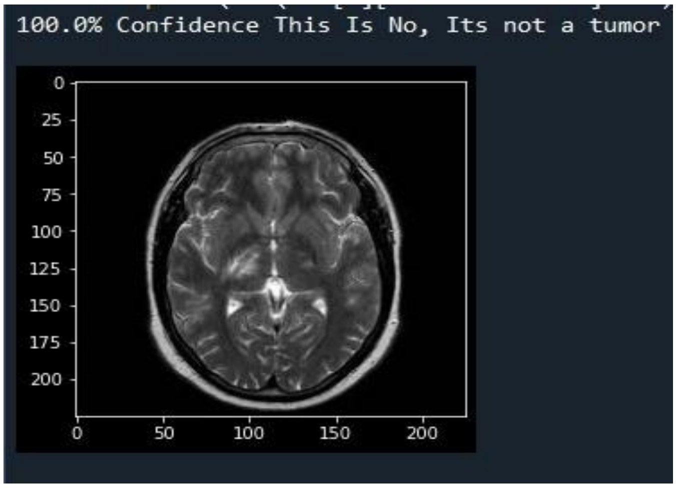

Fig 3.3 Brain Tumor- Negative

IV. CONCLUSION

In conclusion, deep learning for brain MRI segmentation represents a pivotal advancement in the field of medical imaging and neurology. Its current applications have already demonstrated its potential to greatly improve the accuracy and efficiency of brain MRI analysis, particularly in the detection and characterization of neurological conditions such as brain tumors. By automating and enhancing the segmentation of brain structures, deep learning models provide valuable support to healthcare professionals, enabling faster and more precise diagnoses. This technology's impact on patient care is significant, as it not only reduces the potential for human error but also expedites the decision-making process. The ongoing evolution of deep learning techniques in this context promises to make even greater strides in diagnostic capabilities, reinforcing its role as a transformative tool in neuroimaging and neurological healthcare.

V. FUTURE SCOPE

The future of deep learning in brain MRI segmentation holds great promise. As technology and research in this field advance, we anticipate several exciting developments. One key area of growth is enhanced accuracy, with deep learning models becoming even more precise in segmenting various brain structures and anomalies. The integration of multi-modal imaging data, combining MRI with other neuroimaging techniques, will further improve accuracy. Automation and speed are also on the horizon, with future models offering near-real-time segmentation, reducing the time required for diagnosis and treatment planning. This automation will reduce the workload on radiologists, enabling them to focus on more complex tasks. Moreover, customization and personalization of deep learning algorithms will be a prominent trend, accounting for individual patient data and anatomical variations. Interpretability, a current challenge in deep learning, will see improvements, making results more understandable and trustworthy for clinical decision-making. Additionally, seamless integration into clinical workflows will become more widespread, ensuring the practicality and accessibility of deep learning models in healthcare settings. The synergy of deep learning and brain MRI segmentation is set to continue its transformative journey, revolutionizing neurology by enhancing diagnostic accuracy, patient care, and our understanding of neurological disorders.

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