Automated Brain Lobe Segmentation and Feature Extraction from Multiple Sclerosis Lesions Using Deep Learning

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Abstract: This study focuses on automating the segmentation of brain lobes in MRI images of Multiple Sclerosis (MS) lesions to extract crucial features for predicting disability levels. Extracting significant features from MRI images of MS lesions is indeed a complex task due to the variability in lesion characteristics and the detailed nature of MRI images. Furthermore, all these studies required continuous patient monitoring. Therefore, our contribution lies in proposing an approach for the automatic segmentation of brain lobes and the extraction of lesion features (number, size, location, etc.) to predict disability levels in MS patients. To achieve this, we introduced a model inspired by U-Net to perform the segmentation of different brain lobes, aiming to accurately locate the MS lesions. We utilized two private and public databases and achieved an average mean IoU score of 0.70, which can be considered encouraging. Following the segmentation phase, approximately 7200 features were extracted from the MRI scans of MS patients.

1 INTRODUCTION

Multiple sclerosis (MS) is a demyelinating disease of the central nervous system (CNS) characterized by damage to the protective myelin surrounding the nerve fibers within the brain and spinal cord. It primarily affects young adults and leads to increasing disability (Thompson, et al., 2018). Diagnosis is confirmed through magnetic resonance imaging (MRI), with varying contrast in cerebral MRI. MS lesions are surrounded by edema, which appears as a hyperintense signal on the T2 FLAIR image. These lesions can appear in different areas of the brain. They are characterized by their variability in terms of volume, location, shape, subjects, and texture, leading to symptoms that vary depending on where these lesions are located. Consequently, the cerebral lobes are also vulnerable to the impact of MS, as they contain numerous nerve fibers and play a crucial role in various brain functions. So, MS Lesion appears in:

- The temporal lobe can affect vision, touch, memory, hearing, and language comprehension.
- The frontal lobe can lead to issues with emotional control, cognitive functions, planning, decision-making, as well as the supervision of voluntary movements and activities.
- The parietal lobe can disrupt the processing of information related to temperature, taste, touch, and movement.
- The occipital lobe can lead to vision problems, such as visual perception alterations, visual disturbances, and even partial or total vision loss.

Thus, extracting meaningful features from brain lesions to classify these anomalies based on cerebral lobes can provide valuable insights into predicting which human activities or tasks may be affected by these abnormalities. Therefore, to extract these features, a step of segmenting the different cerebral lobes is required to facilitate the localization of brain lesions. However, automatic brain region segmentation is challenging due to variations of brain size and shape from one individual to another, as well as variations in the quality, size, and number of MRI slices. Furthermore, cerebral lobe segmentation is

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typically performed using 3D data, making the use of 2D slices with a reduced number of MRI slices, not an easy task. Indeed, collecting data on multiple sclerosis (MS) can be a challenging task, especially when it involves both imaging and clinical data. To meet our research needs and consider our medical context, we utilized two separate databases: our own database and the public database proposed by (Almutairi, 2022). The characteristics of the two databases are similar, that's why we chose to combine them to perform the segmentation task.

For the segmentation of brain regions, several tools and methods based on machine learning (ML) and Deep Learning (DL) have been proposed, each having its own advantages and disadvantages. In this research, our approach involves utilizing the U-Net architecture to segment the distinct brain lobes. This segmentation aims to facilitate the extraction of features from MS lesions, pinpoint their locations, and predict the disease's progression. The objective of the study is the segmentation of these regions using only 2D data with a limited number of slices.

The structure of this paper is as follows. Related works are detailed in Section 2. Datasets are explained in Section 3. The proposed workflow is detailed in Section 4. Section 5 provides the results of the method we proposed. Finally, Sections 6 closes with a discussion, conclusion and main limitations of this study.

2 RELATED WORKS

Accurate segmentation of MRI images becomes a crucial task for Alzheimer's disease, dementia, partial epilepsy, multiple sclerosis, etc. It has become an important task for many evaluations in neurological research, including the diagnosis, progression and treatment of various neurological diseases such as neurological diseases. Manual segmentation is considered the gold standard in the field of anatomical segmentation. Determining brain structure is time-consuming and detailed because an MRI can consist of hundreds of segments, depending on the resolution of the MRI. Therefore, this labor-intensive method is not suitable for large-scale neuroimaging studies. Automatic segmentation techniques attempt to resolve the limitations associated with manual segmentation.

Following the advancement of algorithms and computing resources several segmentation techniques have been developed. These techniques include (a) FreeSurfer, (b) FMRIB Software Library (FSL), and (c) Statistical Parametric Mapping (SPM) (Singh, 2021)… Moreover, approaches that utilize convolutional neural networks (CNN) are widely employed for automatic segmentation tasks.

Table 1: State of the art of published works on the segmentation of brain structures.

Authors	Model	Application	Description
(Sken, 2016)	FCN with a late fusion method	Tissue segmentation	FCNs for the segmentation of isointense phase brain MR images.
(Klein, 2018)	DeepNAT	Anatomical segmentation	3D Deep convolutional neural network for the automatic segmentation of NeuroAnaTomy.
(Ayed, 2018)	3D CNN	Anatomical segmentation	3D and fully convolutional neural network (CNN) for subcortical brain structure segmentation in MRI.
(Llado, 2019)	FCNN	Tissue segmentation	Eight FCNN architectures inspired by robust stateof-the-art methods on brain segmentation related tasks.
(Tang, 2019)	U-net	Tissue segmentation	Skip-connection U-net for WM hyper intensities segmentation.
(Gao, 2020)	Fuzzy C-mean	Tissue segmentation	Fuzzy C-means framework to brain tissue segmentation

The Table 1 summarizes the different automated segmentation techniques mentioned in the literature.

FreeSurfer is an open-source software. Its focus is on processing 3D images, including full volumetric MR images. It is optimized for segmentation, 3D brain reconstruction, and volumetric analysis from

these types of images. FSL is a comprehensive library of neuroimaging tools for structural, functional, and diffusion tensor imaging (DTI) studies. It is capable of handling a wide range of data and is known for its robustness. SPM is a package developed for the analysis of neuroimaging data coming from several imaging modalities. It is capable of performing complex and detailed statistical analyses, but requires MATLAB platform, volBrain (Online Web Platform) is a web-based pipeline for MRI brain volumetry. Its system is primarily based on a multi-atlas, patch-based segmentation method. Registration is necessary to use this platform, but there is a limit on the number of concurrent jobs that can be submitted. Although it is user-friendly, it does not offer as much as more advanced software, which results in limitations of specific tasks. Although there are a variety of tools to analyze functional and structural imaging, they are not specifically designed for processing 2D data with fewer slices. In addition to the segmentation tools previously presented, there are several works proposed for the segmentation of brain regions based on deep learning. The Table 1 provides a summary of some model. The majority of previous studies have typically aimed to segment various brain tissues, including white matter, gray matter, and cerebrospinal fluid. However, our approach is distinct. Our research focuses on the segmentation of brain lobes, which allows for the precise localization of MS lesions. By concentrating on this specific region of the brain, we can thoroughly evaluate how these lesions impact human cognitive and sensory functions, offering a unique perspective on the consequences of MS.

3 CONSIDERED DATASETS

Two datasets were used: our private MS database and the public database proposed by (Almutairi, 2022),(https://data.mendeley.com/datasets/8bctsm8jz7/1).

3.1 MS Private Dataset

We recruited 22 patients diagnosed with relapsing-remitting multiple sclerosis (RR-MS) and obtained informed consent from the Fattouma Bourguiba University Hospital Ethics Committee. MRI T2-FLAIR image sequences were acquired at the Neurology Department of Fattouma Bourguiba University Hospital in Monastir. Each patient had multiple time-points, ranging from 2 to 4. The dataset was generated using a Philips 1.5T machine (Ingenia, Philips, medical systems, Best, the Netherlands) equipped with a 20-channel phased-array coil for the head, neck, and spine, located at the Fattouma Bourguiba Hospital Medical Imaging Department.

The original images of MS patients varied in dimensions from (352 × 352) to (512 × 512), with a spatial resolution of (0.46 × 0.46) and a slice thickness of 7 mm. Ground truths were meticulously prepared and validated by our highly experienced expert with 16 years of expertise (Figure 2). Among these 22 patients, clinical data is accessible for 19 of them. Demographic and lesion characteristics are detailed in Table 2 and Table 3.

Table 2: Baseline characteristics of MRI Image (Private dataset).

Baseline characteristics (MRI Image)	
Sex ratio (male : female)	0,46 [7:15]
Modality	T2- FLAIR
Image Size	256×256
Number of original images	370
Number of groundtruth	370
Total number of lesions (SD) [min : max]	1716 ± 3.98 [1:26]
Surface area of lesion (mm^2) [min : max] (SD)	[4.0, 859.0] ± 93.63

Table 3: Baseline characteristics of Clinical Data (Private dataset).

Baseline characteristics (Clinical Data)	
Sex ratio (male : female)	0,35 [5:14]
Current age (years) [min : max]	35 ± 9.2 [20 : 50]
Age of onset	8,05 ± 3,48 [3 : 16]
EDSS [min : max]	3,10 ± 2,35 [1 : 8]
Types of Medicines	[1,2,3,4]
Co-moroidity (No/Yes)	(16/3)

3.2 MS Public Dataset

Offered by (Almutairi, 2022) in 2022, this dataset constitutes a valuable resource in the field of multiple sclerosis (MS) (see Table 4 and Table 5). It comprises multi-sequence MRI (1.5 Tesla) data from 60 patients diagnosed with MS, accompanied by a consensus-based manual segmentation of lesions, assessments of disability levels using the Expanded Disability Status Scale (EDSS), general patient information, and relevant clinical data. One of the dataset's standout features is the quality of its manual lesion segmentation. Two expert radiologists and a neurologist, ensuring a high level of accuracy and reliability, performed this segmentation. It covers three crucial MRI sequences: T1-weighted, T2-

weighted, and FLAIR (fluid-attenuated inversion recovery), enabling in-depth analysis of lesion characteristics in various contexts.

Table 4: Baseline characteristics of MRI Image (Prublic dataset).

Baseline characteristics (MRI Images)	
Modalities	T1/T2/T2-FLAIR
Number of OI[5] FLAIR	1446
Number of GT[6] (FLAIR) with at least one lesion	794
Number of OI (T2)	1385
Number of GT[6](T2) with at least one lesion	644
Number of OI (T1)	1358

Table 5: Baseline characteristics of Clinical Data (Public dataset).

Baseline characteristics (Clinical Data)	
Sex ratio (male : female)	0,30 [14:46]
Current age (years) [min : max]	34 ± 12,1 [15 : 56]
Age of onset	29,7 [8 : 52]
EDSS [min : max]	2,26 ± 1,5 [0 : 6]
Types of Medicines	[1,2,3,4,5]
Co-moroidity (No/Yes)	(47/13)

4 PROPOSED WORKFLOW

Our proposed pipline is composed of six steps (Figure 1): (i) Pre-processing to refine images and facilitate brain lobes segmentation, (ii) Clinical data preprocessing to ensure their compatibility with AI algorithms, achieving greater consistency. (iii) Brain lobes Segmentation based on DL architecture, (iv) Automated feature extraction for capturing significant characteristics including lesion Number, lesion size, localization, and lobe area... (v) Creating a file that combines both MRI features and clinical data to identify the most correlated features to the MS patients' disability levels and (vi) EDSS Prediction. Each of these steps will be presented in the following section.

4.1 Pre-Processing

In this phase, we applied preprocessing operations to both the image data and clinical data as follows:

Preprocessing of Image Data

- Skull Stripping: We isolated the region of interest by extracting it from extracranial and non-cerebral tissues.
- Background Reduction: The black background was minimized through cropping operations
- Image Resizing: All MRI images were resized to (256× 256) in order to standardize the database.

Preprocessing of Clinical Data

- Z-Score Normalization: We used the Z-Score method to normalize variables such as age and age of onset. The new value is calculated using the formula $(x - \mu) / \sigma$, where x represents the original value, μ is the mean of the data, and σ is the standard deviation of the data.
- Encoding: We applied encoding to variables such as gender, comorbidities, presenting symptoms, and type of medicines.

4.2 Brain Lobes Segmentation

Automatically segmenting brain lobes presents a complex set of challenges due to the inherent variability in brain shapes, sizes, and abnormalities, as well as the diverse qualities and sizes of brain MRI scans. Traditional methods rely on 3D MRI data, making segmentation with 2D scans particularly complex (Singh, 2021).

Multiclass segmentation is an advanced computer vision task that extends beyond binary segmentation. It categorizes every pixel in an image into distinct classes, allowing for the differentiation of various anatomical structures in medical imaging within an MRI scan, such as the brain, heart, and lungs. For our initial work, we chose to utilize the U-Net (Ronneberger, Fischer, & Brox, 2015) architecture, as it continues to be a reference in the field of medical image segmentation (Liang, 2018) (Wen, 2019). This choice was based on its proven effectiveness and reliability in accurately segmenting medical images. It features an encoding and decoding path, which progressively reduces and increases spatial resolution. U-Net can simultaneously segment multiple classes in a single pass, with each class corresponding to a specific object or region. This capability is crucial for tasks like semantic segmentation, where precise classification of different categories within an image is essential.

[5] Original Image (OI)
[6] Groundtruth (GT)

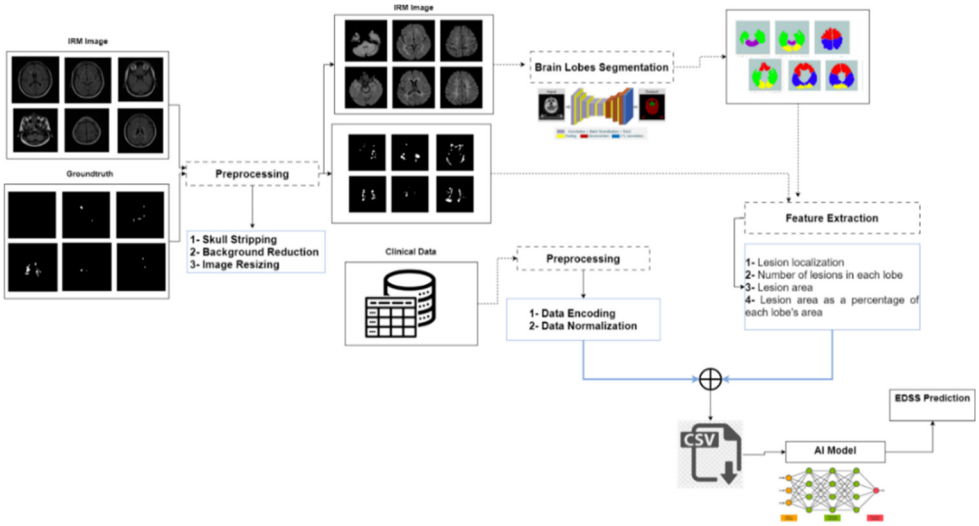

Figure 1: Workflow proposed for Brain Lobes Segmentation and MS lesions features extraction.

U-Net's skip connections maintain spatial information, ensuring accurate segmentation. Consequently, it is a fundamental tool in medical image analysis. To achieve this, we began by preparing the ground truth data for each cerebral lobe in collaboration with our expert. We then proceeded to implement the U-Net model. In total, we had seven classes to segment, which included the Frontal Lobe (FL), Occipital Lobe (OL), Parietal Lobe (PL), Temporal Lobe (TL), Brain Stem (BS), Cerebellum (C), and the background (B). Figure 2 provides an example of the prepared ground truth data. Figure 3 depicts the functioning of each cerebral lobe, highlighting the specific regions and functions of each lobe. This illustration aids in gaining a better understanding of how different parts of the brain interact to control various aspects of cognition, perception, and movement. It serves as a valuable resource for studying MS as it helps us comprehend the potential impacts of lesions on different brain functions.

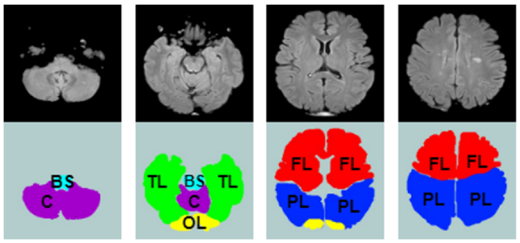

Figure 2: Example of Brain Lobe groundtruth.

U-Net wass proposed by (Ronneberger et al. 2015) in 2015 for biomedical image segmentation. It consisted of a contraction path (downsampling) associated with an expansion path (upsampling). It was proposed to overcome the major limitation of the traditional CNN, which is a compromise between location accuracy, represented by low-level features, and contextual information, provided by higher-level features. During the contraction path, spatial information is reduced while feature information is increased.

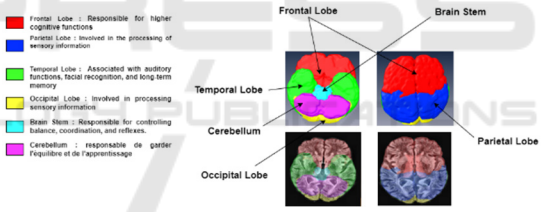

Figure 3: Illustration of the functioning of each cerebral lobe.

However, during expansion, upsampling is performed through the transposed convolutions to build the segmented image. It is characterised by skip connections (concatenation) between these two paths for more accurate retrieval of spatial information. We operated two modifications : (i) Batch Normalisation to speed up learning and produce accurate models. (ii) Dropout between the two consecutive convolutional layers to avoid overfitting (Ronneberger, Fischer, & Brox, 2015). Table 6 sums up the hyper-parameters of convolution and deconvolution layers used in this model. The following notations are used: BN stands for Batch Normalisation and ReLu stands for Rectified Linear Unit. For the implementation of U-Net model, Table 5 sums up the hyper-parameters of convolution and deconvolution layers used in this model.

Table 6: U-Net structure details for the two paths.

Type	Taille/Nombre of filters	Padding	Stride	kernel_initializer	Parameters
Convolution	((3 × 3 × 16) + BN +ReLu) ×2 + Dropout (0.1)	1	1	he_normal	1,946,807
	((3 × 3 × 32) + BN +ReLu) ×2 + Dropout (0.1)				
	((3 × 3 × 64) + BN +ReLu) ×2 + Dropout (0.1)				
	((3 × 3 × 128) + BN +ReLu) ×2 + Dropout (0.1)				
	((3 × 3 × 256) + BN +ReLu) ×2 + Dropout (0.1)				
MaxPooling	(2x2)				
Conv2DTranspose	(2x2)		2		

4.3 Implementation Details

The training phase requires establishing a set of parameters such as the optimiser, learning rate, number of epochs, and batch size . . . These are usually experimentally selected or based on recent studies with the aim of producing precise segmentation performance. The implementation is conducted onIntel Core i9-11900F @ 2.50 GHz, 32Go RAM and a Nvidia GeForce RTX 3090. The suggested models were implemented in Python language using Keras with Tensorflow backend. Table 7 summarizes the hyperparameters used.

Table 7: hyper parameter used in the training step.

Optimizer	Learning rate	Batch_Size	Epochs
ADAM	0.001	16	200

As metrics, we used accuracy, recall, and dice to evaluate the model during training.

$$Accuracy = (TN + TP)/(TP + FP + TN + FN) \quad (1)$$

$$Dice = (2\,TP)/(2TP + FP + FN) \quad (2)$$

$$Recall = TP/(TP + FN) \quad (3)$$

4.4 Feature Extraction Process

McDonalds is considered standard diagnostic criteria for multiple sclerosis (MS) based on clinical, radiological and other medical data. These criteria allow doctors to confirm the diagnosis based on several pieces of evidence such as the patient's symptoms, the results of magnetic resonance imaging (MRI) examinations and other tests. They are used to standardize the diagnostic process and to guarantee consistency. Consistent with these criteria (Skripuletz, 2019), we extracted FLAIR MRI features and specific disease characteristics based on feature types, including lesion location, shape, size, number, and density (Figure 4). To do this, a graphical interface has been developed.

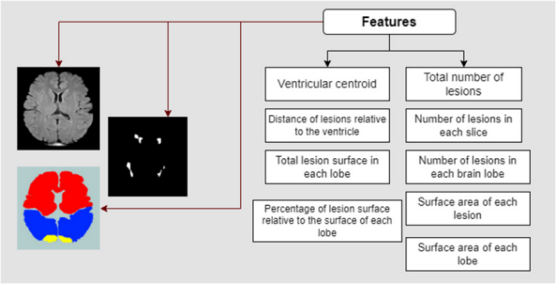

Figure 4: Example of Features extracted from MRI Images.

The main goal of this interface is to make the feature extraction process more accessible to non-technical users or experts in a particular field. This helps speed up the data analysis process, especially when dealing with large amounts of information or complex data.

The proposed extraction steps are as follows:

- Measure the centroid of the ventricle to identify lesions located near the cerebral ventricular system.
- Load the brain lobes and calculate the area of each lobe.
- Segment MS lesions and calculate the area, location and number of each lesion.
- Create a file containing all the features extracted from FLAIR MRIs.
- Integrate clinical data with imaging data to facilitate predictive modeling, ultimately identifying features with the strongest correlations with disability progression.

Figure 5 presents a visual representation of the process we proposed. It allows you to better understand how our methodology works.

For the MS lesion segmentation phase we used our own "Concat-U-Net" method published in (Messaoud, 2022) which makes it possible to segment objects of variable size, location and number such is the case of lesions.

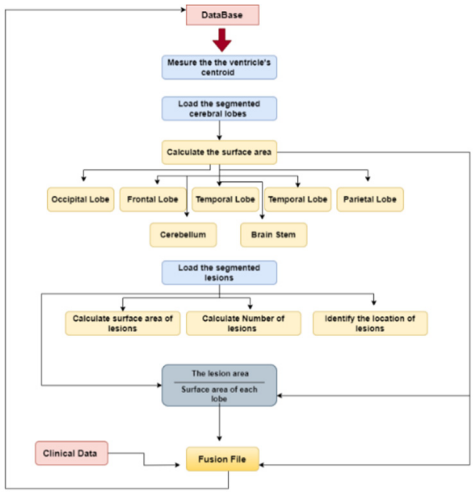

Figure 5: Workflow proposed for the MS lesion features extraction.

5 RESULTS OF BRAIN LOBE SEGMENTATION

In total, we prepared the ground truths of 32 patients. We implemented a nested 5-fold cross-validation over the whole datasets. The training curves of the U-Net model are presented in Figure 6 and Figure 7. The letters S stand for Subject, and the numbers represent the subject identifier. (– denotes the subjects from 1 to N). Using the previously presented 5-Fold cross-validation scheme, we have successfully applied Deep learning to segment the cerebral lobes, even with a limited number of slices for each patient. This approach has significantly improved our ability to accurately locate multiple sclerosis (MS) lesions and estimate their size.

In the works of (Almutairi, 2022), the approach involved segmenting the various brain lobes through a series of steps. These steps included dividing the brain into four subregions, measuring the center, width, and height of each region, and subsequently segmenting each subregion into four additional sections, each of which was labeled accordingly. However, in our case, we utilized a U-Net-inspired architecture to calculate the surface of each cerebral lobe, enabling us to extract the percentage of lesion involvement in the brain lobes. This information could serve as a significant biomarker for multiple sclerosis diagnostic analysis.

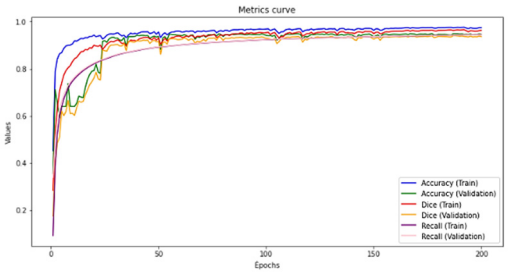

Figure 6: Accuracy, Recall, Dice curves.

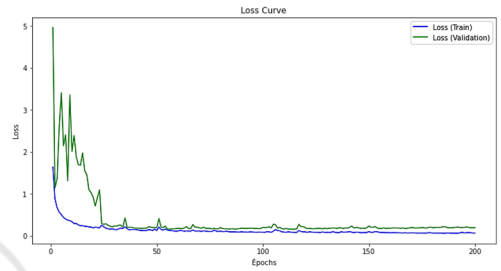

Figure 7: Training loss and Validation Loss curves.

To evaluate the obtained result, we used the Mean Intersection over Union (MeanIoU) is a metric used to assess the accuracy of image segmentation models. It calculates the intersection over the union for each class and then computes the average across all classes. The formula for calculating MeanIoU is as follows:

$$\text{MeanIoU} = \frac{1}{N} = \sum_{I=1}^{n} \left| \frac{P_i \cap G_i}{P_i \cup G_i} \right| \quad (4)$$

The boxplots presented in Figure 8 depict the results for each testing level. As an average result, we achieved a mean IoU (Intersection over Union) score of 0.70, which can be deemed highly encouraging.

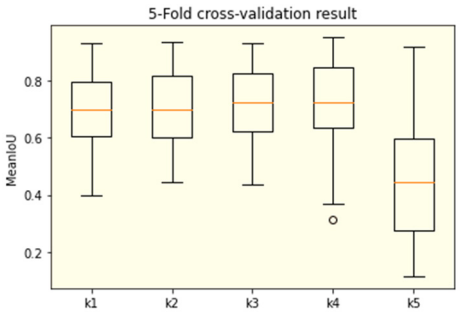

Figure 8: Boxplots showing the performance of tested model with all results obtained.

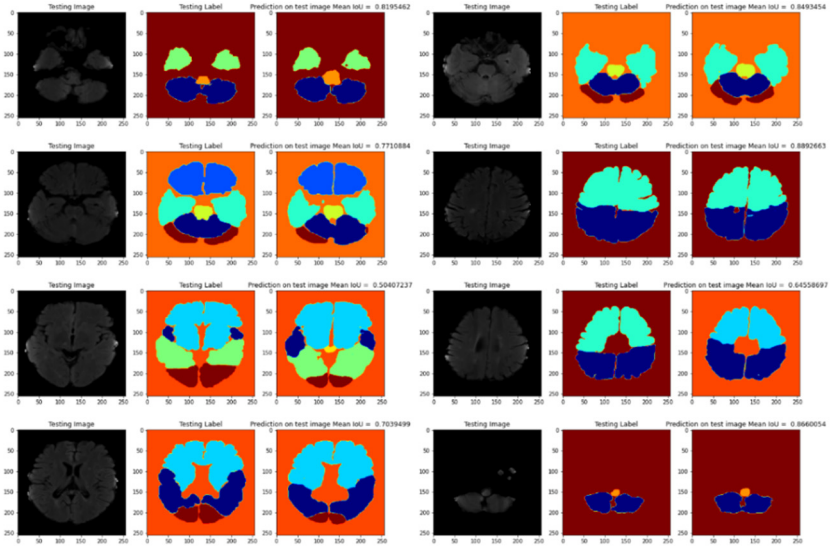

Figure 9: Example of Output segmentation results.

This high score indicates a strong match between the model's predictions and the ground truths, underscoring the effectiveness of our cerebral lobe segmentation approach for assessing multiple sclerosis lesions. This can be readily appreciated in Figure 9, which is also reflected in the measured MeanIoU value of the implemented U-Net. After performing the segmentation of brain regions, we followed the workflow presented in Figure 5 to extract features from MS lesions. These features were then integrated with clinical and demographic data to study the correlation between the features and their impact on the progression of this pathology. In total, we extracted +7200 features. The calculation of these features was performed using the following formula: Total number of features = (Number of features per slice) x (Number of slices per patient) x (Number of patients). The proposed works is published in https://github.com/nadandan/MRI-Brain-Region-Segmentation

6 DISCUSSION AND CONCLUSION

The key contribution of this study is the segmentation of brain lobe regions using only 2D data with a limited number of slices and proposing an automated approach to extract features from MS lesions and combine them with patients' clinical and demographic data. As our initial step, we selected the U-Net architecture, which has demonstrated superior performance in medical image segmentation. We developed a U-Net-inspired model for the segmentation of seven classes: the Frontal Lobe (FL), Occipital Lobe (OL), Parietal Lobe (PL), Temporal Lobe (TL), Brain Stem (BS), Cerebellum (C), and the background (B). This was accomplished using 2D data with a reduced number of slices for each patient. On average, we achieved a highly encouraging mean Intersection over Union (IoU) score of 0.70. Our focus lies in examining the surface, localization, and the number of lesions. Consequently, we successfully extracted approximately 7200 features. In our future work, we intend to utilize the generated feature file (both clinical and image data) from our interface to predict the disability level of MS patients. This study's limitation lies in its exclusive use of the U-Net architecture. It is essential for us to assess other architectures for performance comparison and possibly develop our unique model. Furthermore, expanding the dataset with more images is crucial for improving overall performance.

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