© May 2023| IJIRT | Volume 9 Issue 12 | ISSN: 2349-6002

Brain Tumor MRI Image Segmentation using Deep Learning

Saumya Prasad[1], Muntzar Sayyed[2], Pratik Turkar[3], Ayush Tambe[4], Rashmi Jolhe[5]
[1,2,3,4]Student, Dept. of Information Technology, Datta Meghe College of Engineering, Maharashtra
[5] Asst. Professor, Dept. of Information Technology, Datta Meghe College of Engineering, Maharashtra

Abstract— The proposed work aims to develop a segmentation model using Deep Learning Technique, which is a sub-part of Machine Learning. Using a CNN (Convolutional Neural Networks) model preferably Resnet50 Architecture, we aim to develop a model to detect tumours present in the patients' brain MRI images. Initially, the model will classify the given dataset and segregate into images having tumour and no-tumour. Additionally, the model will highlight the tumour mask in the input image and will display the predicted mask along with the actual mask of the brain tumour. Our project mainly focuses on localization of the tumour and displaying its mask.

Index Terms— Brain tumour, MRI images, Resnet50 Architecture, CNN – Convolutional Neural Networks, Deep Learning

I. INTRODUCTION

Brain tumour MRI image segmentation is a project that involves analysing magnetic resonance imaging (MRI) scans of the brain to identify the location and extent of tumours. The project uses machine learning and computer vision techniques to analyse MRI images and segment the regions of the brain that contain tumours. The goal of the project is to develop an accurate and automated system that can assist radiologists in the diagnosis and treatment of brain tumours. By accurately identifying the location and size of tumours, the system can help doctors plan surgery, radiation therapy, and other treatments. The project involves several steps, including pre-processing of MRI images, feature extraction, and classification of regions of the brain into tumour and non-tumour regions. The system may also incorporate deep learning techniques such as convolutional neural networks (CNNs) to improve segmentation accuracy. Overall, the brain tumour MRI image segmentation project has the potential to improve patient outcomes by providing doctors with more accurate information about the location and extent of brain tumours, enabling more precise and effective treatment.

II. CONCEPTS

A. What is a Brain Tumor?

A brain tumour is an abnormal growth or mass of cells within the brain or the central nervous system. There are two main types of brain tumours: primary and secondary.

Primary brain tumours originate in the brain itself, and are categorized according to the type of cells that they arise from. There are many different types of primary brain tumours, including gliomas, meningiomas, schwannomas, and pituitary adenomas, among others.

Secondary brain tumours, also known as metastatic brain tumours, are tumours that have spread to the brain from other parts of the body, such as the lungs, breast, or colon.

Brain tumors can be benign or malignant, and their symptoms and treatment options depend on various factors, including the type, location, size, and grade of the tumor. Common symptoms of brain tumors include headaches, seizures, cognitive changes, vision problems, and motor deficits.

B. Grayscale Images

A grayscale image is a digital image in which the value of each pixel is represented by a single scalar value, typically an integer between 0 and 255, that corresponds to the intensity of the pixel's brightness or darkness. In other words, a grayscale image is a monochrome image that contains only shades of Gray, ranging from black (0) to white (255).

In a grayscale image, the intensity of each pixel is typically represented by a single value in the range of 0-255, with 0 representing black and 255 representing white. The shades of Gray in between are used to represent the different levels of brightness or darkness in the image.
Grayscale images are widely used in many applications, including medical imaging, photography, and computer vision. They are often used as a simple and efficient way to represent images that do not require the full range of colour information.

C. Convolutional Neural Networks
Convolutional Neural Networks is the long for CNN. It is a type of deep neural network that is commonly used in computer vision tasks, such as image and video recognition, object detection, and segmentation. CNNs are designed to process images in a way that is like how the human visual system works. They consist of multiple layers of interconnected neurons that perform feature extraction, representation learning, and classification. The layers of a CNN typically include convolutional layers, pooling layers, and fully connected layers. They are trained using backpropagation, a gradient-based optimization algorithm, to minimize a loss function that measures the difference between the predicted output and the ground truth. The weights of the filters in the convolutional layers are updated during training to improve the accuracy of the predictions.
It features multiple layers which include convolutional layers, pooling layers, and fully connected layers. The convolutional layers are the key building blocks of a CNN, and they apply a set of filters to the input data, extracting features at different scales and orientations. Each filter is essentially a small matrix of weights that is convolved with the input data, producing a feature map that highlights the presence of certain features in the input.
By stacking multiple convolutional layers, a CNN can learn increasingly complex and abstract representations of the input data.

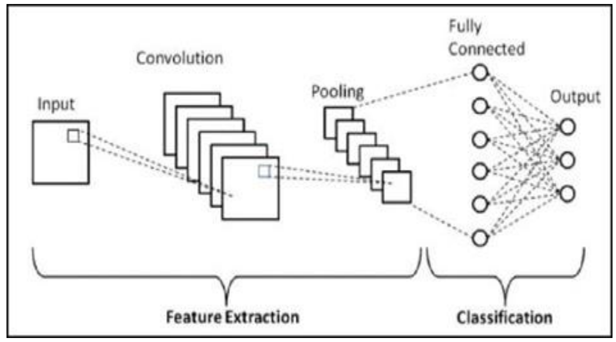

Fig -1: Convolutional Neural Network Architecture

D. Resnet50 Architecture
ResNet-50 is a deep convolutional neural network architecture, which is a variant of the ResNet (Residual Network) architecture that consists of 50 layers, hence the name ResNet-50 It is primarily used for image classification tasks and has achieved state-of-the-art performance on several benchmark datasets, such as ImageNet, BRATS, etc. It uses a series of convolutional layers, pooling layers, and fully connected layers to extract features from images and predict their corresponding labels.
The network is typically trained using a supervised learning approach, where the weights of the filters are adjusted during training to minimize a loss function that measures the difference between the predicted output and the ground truth.

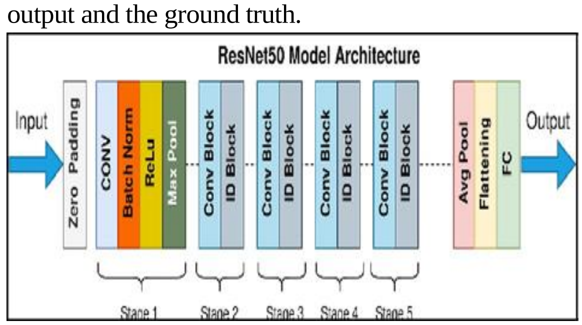

Fig -2: Resnet50 Architecture

E. Pre-Processing Techniques
A. Conversion to Gray Scale Images:
Why do we convert colour images to Grayscale image:
Colour images are typically converted to grayscale images for several reasons, including:
Simplification: Grayscale images have only one channel of information (intensity), whereas colour images have three channels (red, green, and blue).

Converting to grayscale simplifies the image data, making it easier to process and analyse.
Data Reduction: Grayscale images require less memory and storage space than colour images since they have fewer channels of information.
Noise Reduction: Grayscale images are less prone to noise than colour images, which can make image processing and analysis more accurate.
Better contrast: By converting an image to grayscale, the contrast between different parts of the image can be increased, which can make it easier to identify patterns or features.
Computationally Efficient: Grayscale images can be processed more quickly than colour images, making them suitable for applications that require real-time processing, such as video analysis.
Compatibility: Some image analysis algorithms and software tools are designed to work with grayscale images, making it necessary to convert colour images to grayscale before processing.
Overall, converting colour images to grayscale can simplify and enhance image processing, making it easier to analyse and extract useful information from images.

B. Data Augmentation:

Data augmentation is a technique used in machine learning to increase the size of a training dataset by generating new samples from the existing data. In the context of brain tumour MRI segmentation, data augmentation involves applying a set of transformations to the MRI images and corresponding tumour segmentation masks to create new, synthetic training samples.
The goal of data augmentation in brain tumour MRI segmentation is to improve the robustness and generalization of the machine learning model by increasing the diversity of the training data. This can help the model to better capture the variability in the MRI images and segmentation masks that can arise from differences in patient anatomy, image acquisition protocols, and scanner settings.
Examples of common data augmentation techniques used in brain tumour MRI segmentation include:
Rotation: The MRI images and segmentation masks are rotated by a certain angle.
Translation: The MRI images and segmentation masks are shifted by a certain number of pixels in the x and/or y direction.
Scaling: The MRI images and segmentation masks are resized to a different resolution.
Flipping: The MRI images and segmentation masks are flipped horizontally and/or vertically.
Elastic deformation: The MRI images and segmentation masks are deformed elastically, simulating the elastic deformation that can occur during image acquisition.
Data augmentation can be applied in real-time during training or as a pre-processing step to generate a new dataset. By augmenting the training data, the machine learning model can be trained on a more diverse set of data, which can help to improve its accuracy and generalization performance.

C. Feature Extraction:

Feature extraction is the process of selecting and extracting relevant information from the image that can be used to differentiate between different types of tissue in the brain.
This process involves identifying certain characteristics, or features, of the image that are important for classification, such as texture, shape, intensity, and other visual properties. These features are then used as inputs to a machine learning algorithm or other segmentation method to segment the image into different regions corresponding to different types of tissue.
Feature extraction is an important step in brain tumour MRI image segmentation because it helps to reduce the amount of data that needs to be processed, while also improving the accuracy and efficiency of the segmentation process. By extracting only, the most relevant features, it is possible to improve the performance of segmentation algorithms and make them more robust to noise and other artifacts that may be present in the image.

III. LITERATURE SURVEY

1.Classification and characterization of brain tumour MRI by using Gray scaled segmentation and DNN
This paper presented a work on 2D Model using DNN algorithm with an accuracy above 90%. This study of brain MR Images is helpful in brain tumour diagnosis process. This study proposed a model in which deep neural network technique is used with grey scaled segmentation technique. The proposed

work is split into two sections. The initial step is pre-processing, and the second is post-processing. As an input, a dataset of MRI scans of the brain is being used. For the implementation, ten brain MRI images are used, including non-tumour and tumour affected images. The downloaded images are in.gif format, but they must be converted to.png format before they can be used in the MATLAB environment.

2. Brain Tumour Segmentation Based on Deep Learning's Feature Representation

This paper proposed a work on a method based on convolution neural network architecture for predicting and segmenting a cerebral tumour at the same time. The proposal was split into two parts. To begin, in order to avoid using a labelled image, which implies a subject intervention of the specialist, we used a simple binary annotation that reflects the presence or absence of the tumour. Second, the prepared image data were fed into our deep learning model, which produced the final classification; if the classification indicated the presence of a tumour, the brain tumour was segmented using feature representations generated by convolutional neural network architectures. The proposed method was trained on the BraTS 2017 dataset, which included gliomas of various types.

The DWA mechanism considers the effect of the tumour's central location and the brain inside the body. This model showed an accuracy of 91% in tumour classification and a Dice similarity coefficient of 82.35% in tumour segmentation.

3. Brain Tumour Segmentation with Skull Striping and Modified Fuzzy C-Means -

This paper presented a work on using the approach of skull-scripting for tumour segmentation using Fuzzy C-Means and Skull-Scripting Techniques.

was tested on a dataset for brain tumour diagnosis using MR images, which included 253 MRI brain images, 155 of which showed tumours.

Brain tumour segmentation is one of the most researched topics in medical image processing. Diagnosis at an early stage is vital to saving a patient's life. It is difficult to segment the tumour region from an MRI due to the lack of a sharper edge and clearly visible boundaries. To segment out the tumour region, this paper presents a combination of skull stripping methods and modified fuzzy c-means. After denoising, the acquired image is stripped of irrelevant tissues on the outer boundaries. It is then subjected to the Fuzzy C-Means algorithm. When applied to a sample of 100 MRIs, the obtained results were shown to be superior to the standard fuzzy c-means.

4. Brain tumour segmentation based on Deep learning and an attention mechanism using MRI multimodalities brain images -

In order to obtain a flexible and effective brain tumour segmentation system, the paper proposed a pre-processing method that works only on a small portion of the image rather than the entire image. This method reduces computing time while overcoming overfitting issues in a Cascade Deep Learning model. In the second step, a simple and efficient Cascade Convolutional Neural Network (C-ConvNet/C-CNN) is proposed because we are dealing with a smaller portion of brain images in each slice. This C-CNN model mines both local and global features through two distinct paths. A novel Distance-Wise Attention (DWA) mechanism is also introduced to improve brain tumour segmentation accuracy when compared to state-of-the-art models.

5. Image Segmentation Technology and Its Application in Digital Image Processing.

With the rapid advancement of science and technology, digital image processing technology has now become widely used in a variety of fields, image segmentation being among the most important. Image segmentation is a critical intermediate technology in the digital image processing process. To serve high-level applications such as pattern recognition, it relies on the underlying technology of image digital processing. The first step in the study of artificial intelligence is to process the information interaction between the machine and the real world, and the goal of computer vision research is to make the computer have the ability to perceive and understand image information in the same way that humans do. This paper explains the fundamental principles of image segmentation technology, analyses and discusses image segmentation methods, and investigates the application of image segmentation technology in digital image processing.

6. Brain Tumour Analysis Using Deep Learning and VGG-16 Ensembling Learning Approaches.

The purpose of this study was to critically examine the proposed literature solutions, use the Visual Geometry Group (VGG 16) for brain tumour detection, implement a convolutional neural network (CNN) model framework, and set parameters to train the model for this challenge. Because of its simplicity, VGG is used as one of the best CNN models.

Furthermore, the research team devised an efficient method for detecting brain tumours using MRI to aid in making quick, efficient, and precise decisions. Faster CNN used the VGG 16 architecture as a primary network to generate convolutional feature maps, which were then classified to yield tumour region recommendations. Our proposed methodology was tested on a dataset for brain tumour diagnosis using MR images, which included 253 MRI brain images, 155 of which showed tumours.

IV. PROPOSED METHODOLOGY

Our project will segment the Brain MRI scan images using one of the CNN Architectures – Resnet50 model, to help the doctors and clinicians to feasibly locate the tumour in the MRI image.

To start with, we have built a classification model to detect and comprehend whether a tumour is present in the Brain MRI image or not. If we understand that the tumour is present in the given image, then we proceed further to pre-process the images by utilizing various image pre-processing techniques such as, converting the colourful MRI images to Grayscale images, Data Augmentation for creating multiple copies of the patients' MRI scans, lastly and Feature extraction for extracting relevant features from the image in order to train the model accordingly.

Furthermore, we have built a segmentation model where all the MRI images having tumour will be forwarded to in order to process the given images for finding the tumour location in them, using relevant features extracted from the given MRI images dataset. The dataset we have used is called 'L GG Brain Segmentation' from Kaggle.

Moving further, the segmentation model will predict the tumour location and will display its mask.

Therefore, our project will display predicted tumour mask along with the actual tumour mask in two columns. To summarize our project, we have built two models – one for classification and another one for segmentation i.e., detecting brain tumour in the MRI image and finding its true location according to the pre-trained CNN model using relevant features. The project will also display the accuracy and loss graph for the same.

Dataset Screenshot

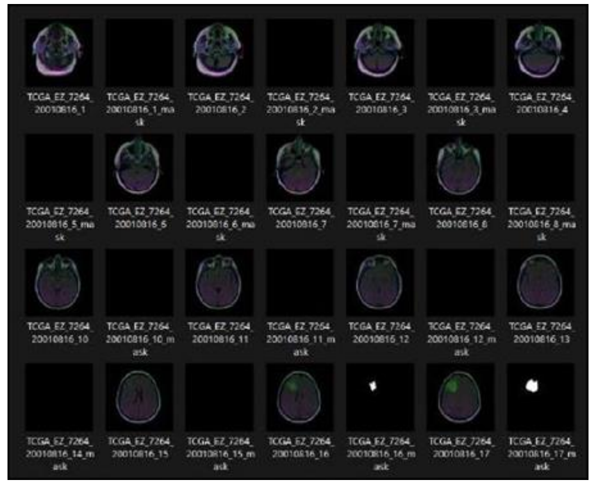

Fig -3: Dataset Screenshot

V. OBJECTIVES

The project aims to develop an accurate, robust, and reliable deep learning model for Brain Tumour MRI Image Segmentation, which can help clinicians diagnose and treat brain tumours more effectively.

VI. BLOCK DIAGRAM

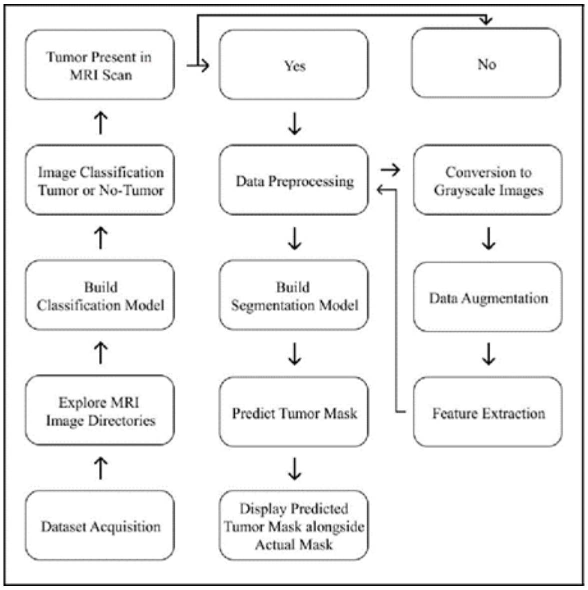

Fig -4: Block Diagram

VII. SCOPE OF THE PROJECT

1.Improving the accuracy and efficiency of brain tumour diagnosis and treatment planning by developing more accurate and efficient deep learning models for MRI image segmentation.

2.Integrating deep learning models into clinical workflows to aid healthcare providers in the diagnosis and treatment of brain tumours.

3.Developing new deep learning architectures and techniques that can improve the accuracy and interpretability of segmentation results.

4.Exploring the use of deep learning for the segmentation of other medical images, such as CT scans and PET scans.

5.Investigating the use of deep learning models for the prediction of patient outcomes based on MRI image segmentation results.

6.Developing new data augmentation techniques to account for variations in MRI scans and improve the robustness of deep learning models.

7.Investigating the use of transfer learning techniques to improve the accuracy and efficiency of deep learning models for MRI image segmentation.

Overall, the scope of brain tumor MRI image segmentation using deep learning is broad and encompasses several areas of research and application. The continued development and refinement of deep learning models for MRI image segmentation will likely have significant implications for the diagnosis and treatment of brain tumors in the years to come.

VIII. RESULT

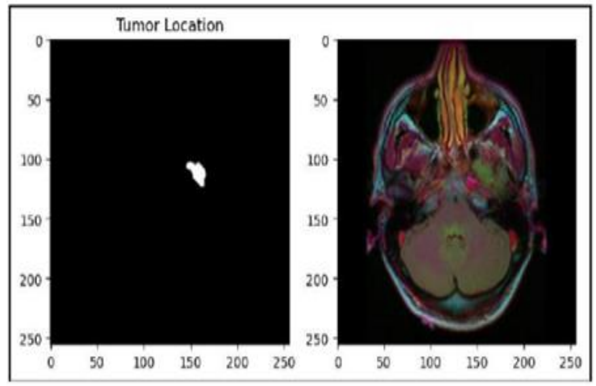

Fig -5 MRI image having tumour along with its mask

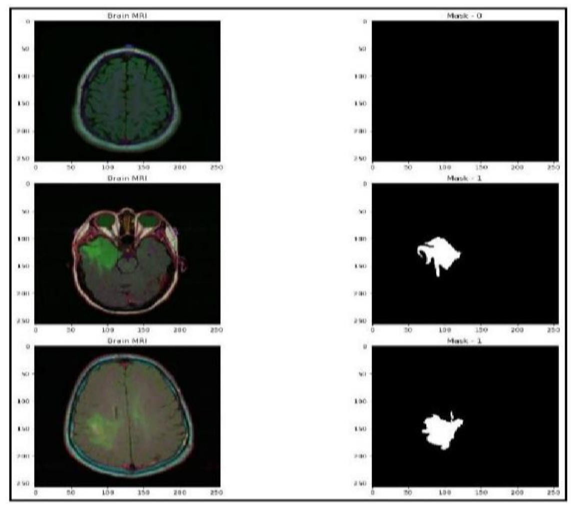

Fig -6 Classification of MRI images into brain having tumour and no-tumour

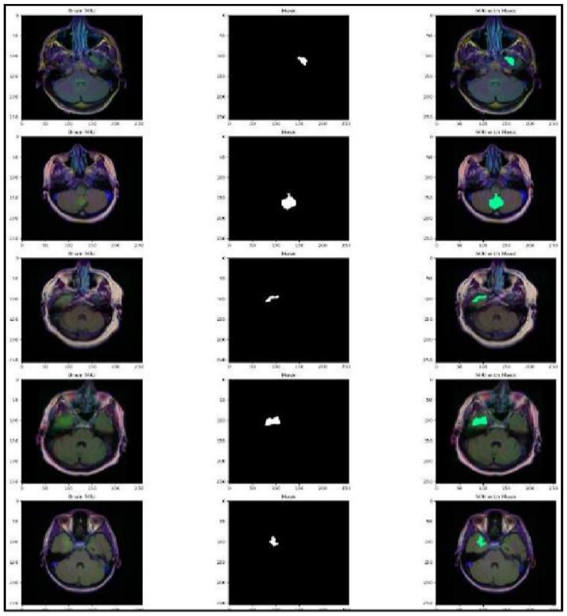

Fig -7 MRI image having tumour along with its mask superimposed on it

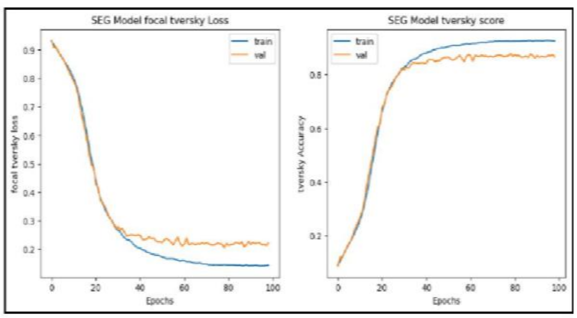

Fig -8 Loss Graph

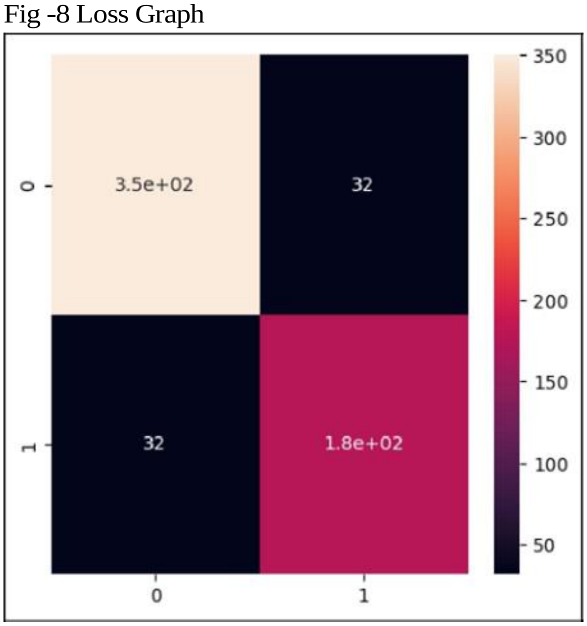

Fig -9 Confusion Matrix

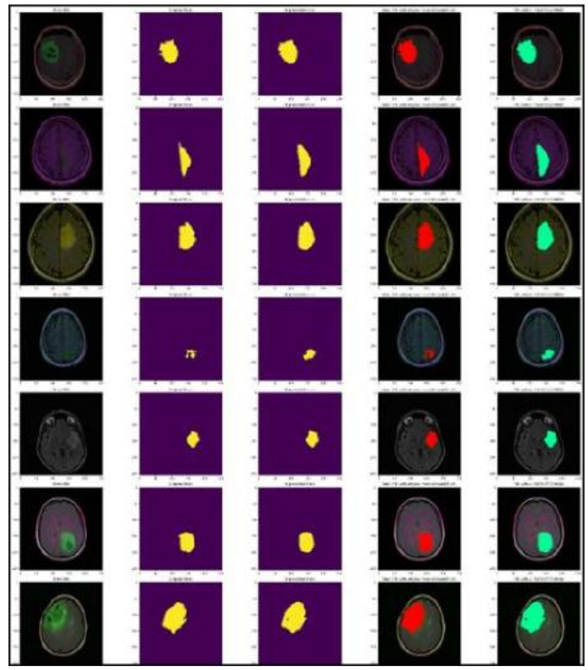

Fig -10 Segmentation Model - Actual vs Predicted tumour masks

IX. CONCLUSION

In conclusion, brain MRI image segmentation using deep learning has shown great promise in accurately identifying and delineating tumour regions in MRI scans. The application of deep learning techniques in medical imaging has revolutionized the field of radiology, allowing for faster and more accurate diagnosis and treatment planning.

The success of deep learning-based segmentation methods is dependent on the availability of large and diverse datasets, along with careful pre-processing and annotation of the data. Advances in hardware and software technologies have enabled the development of deep learning models with high accuracy and efficiency, allowing for the analysis of large volumes of medical imaging data.

Despite the promising results, there are still challenges in the development and application of deep learning-based segmentation methods. One challenge is the need for robust and interpretable models that can handle variations in the data and generalize to new patients. Another challenge is the need for ethical and regulatory frameworks that ensure patient privacy and data security.

Overall, brain MRI image segmentation using deep learning holds great potential for improving the accuracy and efficiency of diagnosis and treatment planning for brain tumours. Ongoing research in this area will likely lead to further improvements in the development and application of deep learning-based segmentation methods in medical imaging.

REFERENCE

[1] Kumar, D.V.; Krishniah, V.J.R. Segmentation of Brain Tumor Using K-Means Clustering Algorithm. J. Eng. Appl. Sci.2018, 13, 3942– 3945.

[2] López, M.M.; Frederick, J.M.; Ventura, J. Evaluation of MRI Denoising Methods Using Unsupervised Learning. Front. Artif. Intell. 2021, 4.

[3] Matthew D. Zeiler, Rob Fergus, Stochastic Pooling for Regularization of Deep Convolutional Neural Networks.

[4] Tahir, Muhammad Naeem. "Classification and characterization of brain tumor MRI by using gray scaled segmentation and DNN." (2018).

[5] Bilenia, Aniket, Daksh Sharma, Himanshu Raj, Rahul Raman, and Mahua Bhattacharya. "Brain tumor segmentation with skull stripping and modified fuzzy C-means." In Information and Communication Technology for Intelligent Systems: Proceedings of ICTIS 2018, Volume 1, pp. 229-237. Springer Singapore, 2019.

[6] Aboussaleh, Ilyasse, Jamal Riffi, Adnane Mohamed Mahraz, and Hamid Tairi. "Brain tumor segmentation based on deep learning's feature representation." Journal of Imaging 7, no. 12 (2021): 269.

[7] Ranjbarzadeh, Ramin, Abbas Bagherian Kasgari, Saeid Jafarzadeh Ghoushchi, Shokofeh Anari, Maryam Naseri, and Malika Bendechache. "Brain tumour segmentation based on deep learning and an attention mechanism using MRI multi-modalities brain images." Scientific Reports 11, no. 1 (2021): 1-17.

[8] Sharma, Komal, Akwinder Kaur, and Shruti Gujral. "A review on various brain tumour detection techniques in brain MRI images." IOSR Journal of Engineering (IOSRJEN) 4, no. 05 (2014): 06-12.

[9] Singh, Amritpal. "Detection of brain tumour in MRI images, using combination of fuzzy c-means and SVM." In 2015 2nd international conference on signal processing and integrated networks (SPIN), pp. 98-102. IEEE, 2015.

[10] Tjahyaningtijas, Hapsari Peni Agustin. "Brain tumour image segmentation in MRI image." In IOP Conference series: materials science and engineering, vol. 336, no. 1, p. 012012. IOP Publishing, 2018.

[11] Fig. 1 Convolutional Neural Network CNN. (n.d.).https://www.google.com/url?sa=i&url=https%3 A%2F%2Fwww.upgrad.com%2 Fblog %2Fbasic-cnn-architecture%2F&psig=AOvVaw3koqbVjejYx-mAy_1 -RKtK&ust=1680265643840000&source=images&cd=v fe&ved=0CBEQjhxqFwoTCNjN7LTTg_4CFQAAAA AdAAAAABAE

[12] Fig. 2 Resnet50 Architecture https://cdn-images-1.medium.com/v2/resize:fill:1600:480/gravity:fp:0.5:0.4/0*tH9evuOFqk8F41FG.png