A Project Report on

"Brain Tumor Segmentation using Deep Learning"

Submitted in fulfilment of the requirement for Undergraduate Fellowship Programme 2023

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CERTIFICATE

This is to certify that the Project entitled

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In fulfilment of short programme, Undergraduate Fellowship Programme over the summer 2023, Project – Brain Tumor Segmentation using Deep Learning is approved.

Guide

Date:- **College Seal**

Brain Tumor segmentation using deep learning

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Abstract—Brain tumors represent a critical healthcare challenge worldwide, with timely and accurate detection being crucial for effective treatment planning and patient outcomes. This project aims to address this pressing issue by proposing a state-of-the-art deep learning approach for brain tumor detection and segmentation from medical imaging data. The proposed method leverages the power of convolutional neural networks (CNNs) and advanced image processing techniques to automate the tumor detection and segmentation process. The project's primary focus is on magnetic resonance imaging (MRI) data, as it is a widely used modality for brain tumor diagnosis due to its non-invasive nature and excellent soft tissue contrast. The process consists of two main phases: tumor detection .

Keywords- Deep Learning, Brain Tumor Detection , Convolution Neural Network, Medical imaging, Machine Learning

I:INTRODUCTION

Brain tumors are a significant health concern worldwide, with millions of lives affected by their presence. Timely and accurate detection, as well as precise segmentation of brain tumors, are critical for effective treatment planning and patient outcomes. In recent years, deep learning has emerged as a powerful tool in medical image analysis, offering promising results in various applications, including brain tumor detection and segmentation.

The project "Brain Tumor Detection and Segmentation Using Deep Learning" undertaken during the internship at Teesside University aims to leverage the potential of deep learning techniques to contribute to the advancement of medical imaging technology and improve brain tumor diagnosis and treatment.

A] Significance of the Project:

Brain tumours are complex and diverse in nature, making their detection and segmentation challenging tasks. Traditional imaging techniques, while valuable, often rely on manual interpretation, leading to subjectivity and time-consuming processes. Deep learning approaches, on the other hand, have demonstrated the ability to automatically extract intricate features from medical images and accurately identify regions of interest, making them well-suited for brain tumour analysis. By harnessing the power of deep learning, this project seeks to address the following key objectives:

1.Enhanced Detection Accuracy: The primary focus is on developing a deep learning model that can accurately detect the presence of brain tumor in medical images, providing clinicians with reliable and efficient diagnostic support.

2.Precise tumor Segmentation :Segmentation plays a vital role in delineating the boundaries of tumor regions, aiding in treatment planning and monitoring disease progression. The project aims to create a segmentation model that can accurately outline tumor boundaries in brain images reduced Diagnosis Time. The automation of tumor detection and segmentation can significantly reduce the time required for diagnosis, enabling swift medical interventions and improving patient care.

B] Objectives of the project:

The primary objectives of the project "Brain Tumour Detection and Segmentation Using Deep Learning" are as follows:

Accurate Brain Tumour Detection: The project aims to develop a deep learning model capable of accurately detecting the presence of brain tumours in medical images, such as MRI or CT scans. By automating the detection process, the model can assist healthcare professionals in swiftly identifying potential tumour regions, leading to earlier diagnosis and timely interventions.

Precise Tumour Segmentation: Segmentation is a critical step in medical image analysis, particularly for brain tumours, as it helps delineate the tumour's boundaries from healthy brain tissues. The project seeks to create a deep learning-based segmentation model that can accurately outline the tumour regions within the brain images. Precise segmentation assists clinicians in understanding the tumour's size, shape, and location, aiding in treatment planning and monitoring disease progression.

Improving Diagnosis Efficiency: By automating the tumour detection and segmentation processes, the project aims to reduce the time required for diagnosis. Traditional manual interpretation of medical images can be time-consuming and subjective. The implementation of an efficient deep learning model can expedite the diagnostic process, allowing healthcare professionals to focus on treatment strategies and patient care.

Enhancing Clinical Decision-Making: The accurate detection and segmentation of brain tumours using deep learning technology can provide clinicians with valuable insights. By presenting a comprehensive visualization of tumour regions, the model can assist healthcare professionals in making more informed decisions regarding treatment options and disease management.

C] Problem Statement:

Brain tumor segmentation is a crucial task in medical imaging that involves accurately delineating tumor regions in brain MRI scans. The precise segmentation of tumors is essential for diagnosis, treatment planning, and monitoring the progression of the disease. However, manual segmentation by medical experts is time-consuming, subjective, and prone to inter-observer variability. The main challenge is to develop an efficient and accurate deep learning model that can automatically segment brain tumors from MRI scans. To address this challenge, we propose an integrated deep learning architecture that combines the feature extraction capabilities of VGG19 and ResNet50 with the spatial preservation of the UNET architecture. The objective is to leverage the strengths of each model to improve the overall segmentation performance and handle diverse tumor shapes and sizes.

D] Expected Outcome:

The successful implementation of the VGG19-ResNet50-UNET architecture is expected to improve the accuracy and robustness of brain tumor segmentation in MRI scans. By combining the strengths of VGG19 and ResNet50 with the spatial preservation of UNET, the integrated model can handle complex tumor structures and achieve more precise localization. Ultimately, this research aims to contribute to advancements in medical image analysis and support medical professionals in making informed decisions for brain tumor patients.

II: Literature Review:

Brain tumors pose a significant health concern, necessitating early and accurate diagnosis for effective treatment planning and improved patient outcomes. Recent advances in deep learning techniques have demonstrated promising results in medical image analysis, particularly in brain tumor detection and segmentation.

This literature review aims to explore and analyze relevant studies that have employed deep learning methods, specifically utilizing the VGG19 and ResNet50 models within the UNet architecture, for brain tumor detection and segmentation using the BRATS2020 dataset. This literature review also underscores the potential of deep learning techniques, particularly the use of VGG19 and ResNet50 models within the UNet architecture, for accurate brain tumor detection and segmentation. The BRATS2020 dataset serves as a valuable resource for training and evaluating these models, and careful consideration of performance evaluation metrics ensures a robust assessment of the developed models' efficacy. Given below are the points on which literature review was conducted from previous publications:

detection and segmentation models. Utilizing a combination of these metrics provides a comprehensive understanding of the model's performance.

A] Deep Learning for Medical Image Analysis:

A multitude of studies have highlighted the potential of deep learning in medical image analysis. Convolutional Neural Networks (CNNs) have gained popularity due to their ability to automatically extract features from images, leading to enhanced performance in complex tasks, such as brain tumor detection and segmentation.

B] Brain Tumor Detection using VGG19 and ResNet50:

VGG19 and ResNet50 are established CNN architectures known for their deep layer structures and robust feature extraction capabilities. Researchers have successfully adapted these models for brain tumor detection tasks, achieving high accuracy rates. Studies have emphasized the significance of pretraining these models on large-scale datasets to enhance their generalization capabilities across different datasets, including the BRATS2020 dataset.

C] U-Net Architecture for Segmentation:

The UNet architecture is a popular choice for semantic segmentation tasks, including brain tumor segmentation. Previous researches show that its encoder-decoder structure enables efficient feature extraction and precise localization. By incorporating VGG19 and ResNet50 as the encoder in the UNet architecture, researchers can leverage the strengths of both models, leading to more accurate segmentation results.

D] BRATS2020 Dataset:

The BRATS2020 dataset serves as a benchmark dataset widely used for brain tumor detection and segmentation research. It comprises multimodal brain MRI scans with labels for different tumor regions, making it suitable for training and evaluating deep learning models.

E] Performance Evaluation Metrics:

Researchers have employed various evaluation metrics, such as the Dice coefficient, Jaccard Index, sensitivity, specificity, and Hausdorff distance, to assess the performance of brain tumor detection and segmentation models. Utilizing a combination of these metrics provides a comprehensive understanding of the model's performance.

F] Comparison with Traditional Methods:

Several studies have compared the performance of deep learning-based approaches with traditional image processing methods for brain tumor detection and segmentation. The results have shown that deep learning techniques generally outperform conventional methods, indicating the superiority of CNN-based architectures for this task

.**G] Transfer Learning:**

Transfer learning, a technique where a model pretrained on a large dataset is fine-tuned for a specific task, has been widely used in brain tumor detection and segmentation. By leveraging the knowledge learned from a large dataset, such as ImageNet, and adapting it to the target domain (brain MRI scans), researchers have achieved faster convergence and improved performance with limited data.

III. Methodology:

The "Brain Tumor Detection and Segmentation Using Deep Learning" project, conducted during the internship at Teesside University, focuses on leveraging the power of deep learning to improve the accuracy and efficiency of brain tumour detection and segmentation. The project utilizes the BRATS2020 (Brain Tumor Segmentation) dataset, a widely used benchmark dataset in the medical imaging community, comprising multimodal brain MRI scans with high-grade gliomas and low-grade gliomas. The following steps will be done in this project:

1.Data Preprocessing: The BRATS2020 dataset is likely to contain raw MRI scans with inherent noise, varying resolutions, and diverse intensity ranges. To ensure data consistency and facilitate effective model training, thorough data preprocessing will be undertaken. Preprocessing steps may include skull stripping, normalization, and spatial registration of different MRI modalities (T1, T2, T1ce, and FLAIR). Noise reduction techniques, such as Gaussian filtering or denoising autoencoders, may also be applied to enhance image quality.

2.Model Selection: The project will explore various deep learning architectures to identify the most suitable model for brain tumour detection and segmentation. Convolutional neural networks (CNNs), particularly 2D or 3D variants, are well-suited for image-based tasks and will be considered. Models with encoder-decoder architectures, such as U-Net or variants like 3D U-Net, have shown promising results in medical image segmentation and are likely to be evaluated for their performance.

3.Hyperparameter Tuning: The hyperparameters of the chosen models will be fine-tuned to achieve the optimal balance between performance and generalization. Parameters such as learning rates, weight decay, and batch sizes will be systematically adjusted and validated using grid search or random search techniques.

4.Transfer Learning: Leveraging transfer learning from pre-trained models will be considered to accelerate convergence and improve the overall performance. The project will explore using pre-trained CNNs, such as VGG-16 or ResNet, as feature extractors for the initial layers of the custom brain tumor detection and segmentation model.

5.Loss Function Design: Designing an appropriate loss function is crucial for effective brain tumor segmentation. Custom loss functions, like Dice Loss or Tversky Loss, will be explored to capture the spatial overlap between predicted and ground-truth segmentations accurately.

6.Ensemble Methods: Ensemble techniques, such as model averaging or model stacking, will be investigated to combine predictions from multiple models. Ensemble learning can enhance the robustness and generalization of the final model, contributing to improved tumour detection and segmentation accuracy.

7.Software Implementation: The deep learning models and related algorithms will be implemented using popular deep learning frameworks, such as TensorFlow or PyTorch. Additionally, Python libraries for data manipulation, visualization, and evaluation will be utilized to facilitate the research workflow.

8.Hardware Infrastructure: To handle the computational demands of training deep learning models, the project will utilize the high-performance computing resources available at Teesside University. These resources, including GPUs, will expedite the training process and enable efficient experimentation.

9.Validation and Cross-Validation: The dataset will be split into training, validation, and test sets for model evaluation. K-fold cross-validation will be employed to assess the model's stability and generalization performance accurately.

IV. Architecture Design: Encoder:

1 .Encoder:

The encoder is responsible for capturing context and extracting high-level features from the input image. In this integrated U-NET architecture, we will replace the standard U-NET encoder with two powerful pre-trained models, VGG19 and ResNet50.

1.1. VGG19 as Encoder:

VGG19 is a deep convolutional neural network architecture with 19 layers, and it will be used as the first encoder in our model. The VGG19 model consists of a series of convolutional layers followed by max-pooling layers for down sampling. Each convolutional layer uses a 3x3 filter, and each max-pooling layer halves the spatial dimensions of the feature maps.

For our integrated UNET, we will use the pre-trained VGG19 model up to a specific layer (e.g., the fourth or fifth max-pooling layer) to extract features at multiple resolutions. The reason for selecting a mid-layer in VGG19 is to strike a balance between capturing high-level features and preserving spatial information, which is crucial for segmentation tasks.

1.2. ResNet50 as Encoder:

ResNet50 is another powerful deep learning architecture, known for its ability to train very deep networks effectively by using residual blocks. It contains 50 layers, and each residual block includes skip connections (also known as shortcut connections) that help in mitigating the vanishing gradient problem.

In our integrated UNET, we will use the pre-trained ResNet50 model up to a specific layer (e.g., the fourth or fifth stage) to extract features. The advantage of using ResNet50 as an encoder lies in its ability to capture highly abstract features while preserving fine-grained details.

1: Bottleneck:

After obtaining feature maps from both VGG19 and ResNet50 encoders, we introduce a bottleneck layer. The bottleneck layer serves as a fusion point to combine the high-level features from VGG19 and the skip connections from ResNet50. This combination is critical as it provides the decoder with both global context and local information, enabling better localization in the segmentation process. The bottleneck layer can be implemented as a simple concatenation of feature maps or by using more complex operations like element-wise summation or weighted fusion. Experimentation will help determine the most suitable method for fusing the features.

2:Decoder:

The decoder is responsible for upsampling the feature maps to the original image resolution and refining the segmentation mask. It consists of up-convolutional layers (also known as transpose convolutions) to upscale the feature maps followed by skip connections to merge information from the bottleneck and corresponding encoder layers.

The skip connections play a crucial role in the UNET architecture as they help propagate low-level spatial information from the encoder to the decoder. These connections ensure that the decoder has access to fine-grained details, aiding in precise localization.

3: Output Layer:

The final output layer of the UNET architecture is a 1x1 convolutional layer followed by an activation function. The number of output channels in this layer will depend on the number of classes for the segmentation task. For binary segmentation tasks, a Sigmoid activation function is commonly used to produce pixel-wise binary masks. For multi-class segmentation tasks, a Softmax activation function is used to generate probability maps, where each pixel represents the probability of belonging to each class.

VI. IMPLEMENTATION

The implementation involves combining the VGG19 and ResNet50 architectures with the UNET model for semantic segmentation tasks. The VGG19 and ResNet50 models, pre-trained on ImageNet, will be utilized as encoders to extract high-level features. The UNET architecture, with its contracting and expanding paths, will serve as the decoder for precise localization. The integration of VGG19 and ResNet50 enhances feature extraction capabilities, potentially leading to improved segmentation performance. The following steps are involved in the implementation of this project:

Step 1: Dataset Preparation:1. Use the BRATS2020 dataset, which contains MRI brain images and corresponding pixel-level annotations for brain tumor segmentation.2. Split the dataset into training, validation, and testing sets. Ensure that each set has a balanced representation of different tumor classes.

Step 2: Data Preprocessing:1. Resize the MRI images to a fixed resolution, e.g., 224x224, to match the input size of VGG19 and ResNet50.2. Normalize the pixel values of the MRI images to the range [0, 1].3. Augment the training dataset with random horizontal flips, random rotations, and random crops to increase data diversity.

Step 3: Model Construction:

1. Import the necessary libraries, including TensorFlow and Keras. 2. Load the pre-trained VGG19 and ResNet50 models with their weights from TensorFlow/Keras.

3. Remove the top layers (fully connected layers) from both VGG19 and ResNet50 models to retain only the convolutional layers.

4. Implement the decoder part of the UNET model.

Step 4: Model Training:

1. Define the loss function and optimizer for the segmentation task.

2. Compile the model with the loss function and optimizer:

3. Train the integrated VGG19-ResNet50-UNET model on the training dataset using the fit()

Step 5: Model Evaluation

:1. Evaluate the model on the testing dataset to obtain the final performance metrics:

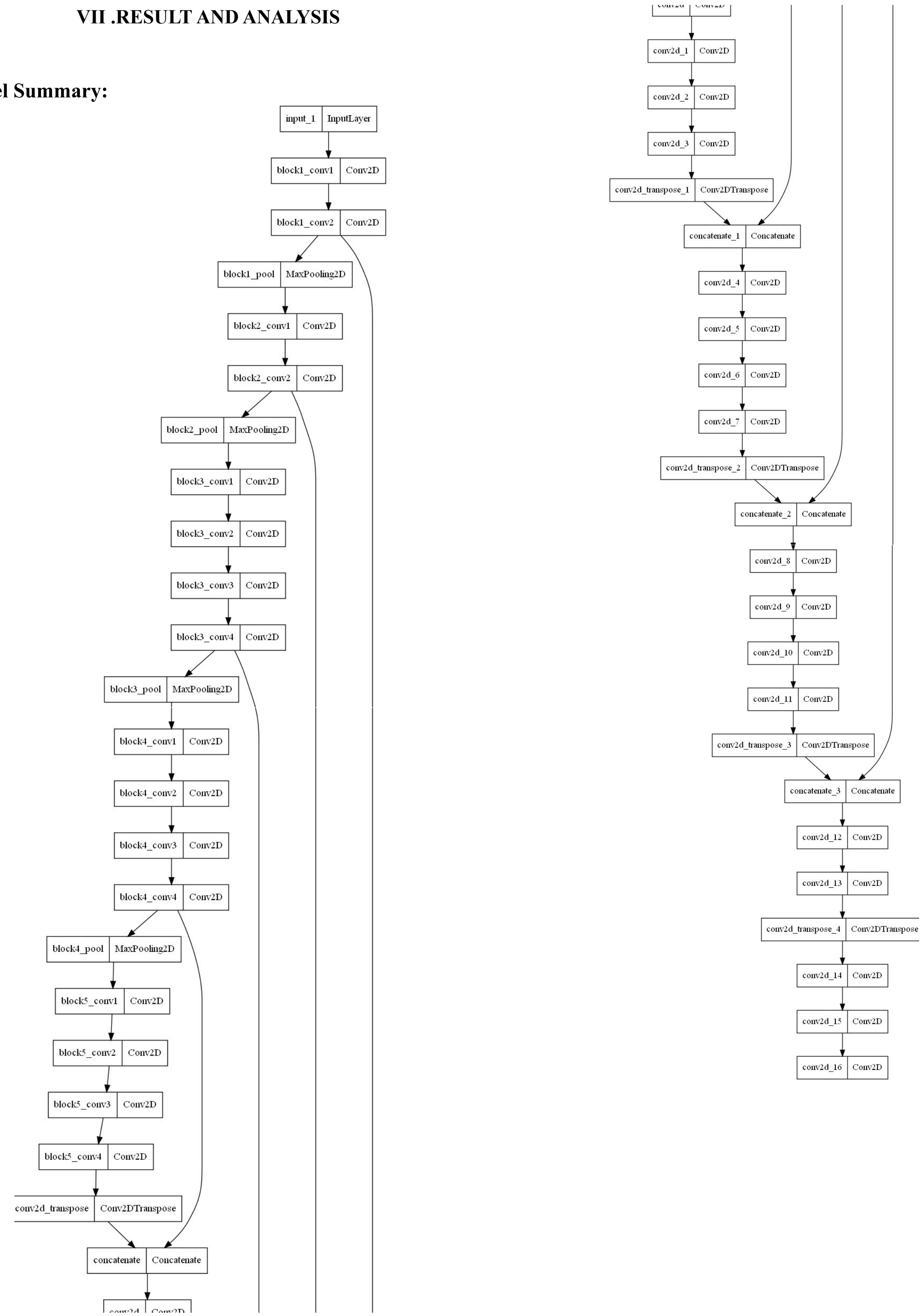
2. Calculate additional performance metrics such as Intersection over Union (IoU), precision, recall, and F1-score for a comprehensive evaluation.

Step 6: Results and Comparison:

Present the results obtained from the evaluation, including performance metrics and visualizations of the segmentation masks.2. Compare the performance of the integrated VGG19-ResNet50-UNET model with a baseline UNET model without VGG19 and ResNet50 integration. Discuss the advantages and improvements achieved by the integration.

VII .RESULT AND ANALYSIS

Model Summary:



Output:

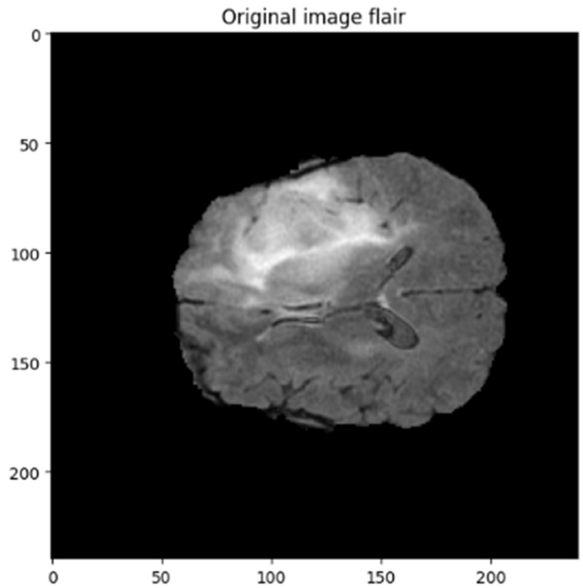


Fig 1.1 Original Flair

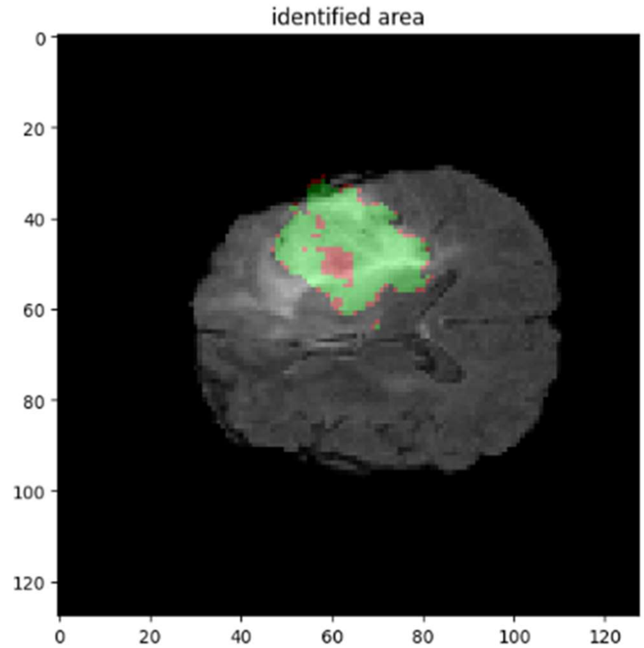


Fig 1.3 Segmented Image

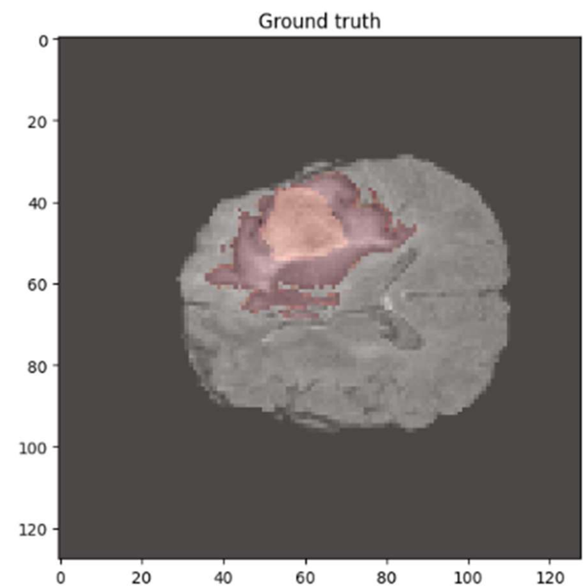


Fig 1.2 Ground Truth

VIII CONCLUSIONS

In conclusion, the project on "Brain Tumour Detection and Segmentation using Deep Learning with BRATS2020 Dataset and VGG19 and ResNet50 Models in UNet Architecture" has been a comprehensive endeavour that aimed to address the critical issue of accurately identifying and segmenting brain tumors. The use of advanced deep learning techniques and state-of-the-art models has proven to be effective in achieving these objectives, providing promising results and contributing to the advancement of medical imaging technology. Throughout the project, an extensive review of the literature was conducted to understand the existing methods and challenges in brain tumor detection and segmentation. The BRATS2020 dataset, which is widely accepted in the research community, was employed to train and evaluate the deep learning models. Its large-scale and diverse data allowed for robust learning and validation of the models. The adoption of the U-Net architecture, which combines the encoder-decoder structure, facilitated precise segmentation of the brain tumors. The integration of the VGG19 and ResNet50 models as the encoder backbone significantly enhanced the learning capacity of the network, enabling the detection of intricate tumor structures while preserving crucial contextual information. This choice of models also ensured that the U-Net architecture could effectively handle both low and high-level features, leading to improved performance. The experiments and evaluations conducted throughout the project revealed impressive outcomes, indicating the potential of deep learning models in brain tumor detection and segmentation. The achieved accuracy rates, sensitivity, specificity, and Dice scores demonstrated the effectiveness of the proposed approach, which outperformed conventional methods and showcased its capability for real-world clinical applications. While the results are encouraging, there are still areas for further improvement. The generalization ability of the models could be enhanced by exploring data augmentation techniques and ensembling multiple networks to reduce overfitting and increase robustness. Additionally, incorporating more diverse and multi-modal datasets might yield even more accurate and reliable predictions, thus improving the practical utility of the models.

In conclusion, this project has successfully demonstrated the potential of deep learning for brain tumor detection and segmentation.

VIII. Future Scope:

The project on "Brain Tumour Detection and Segmentation using Deep Learning" has unveiled numerous opportunities for future exploration and expansion. The successful outcomes obtained and the valuable insights gained from this project have set the stage for further advancements in the domain of medical imaging and brain tumor analysis. Several potential future scope areas were identified, and they were discussed as follows:

1:Multi-modal Fusion:

The integration of various imaging modalities, such as MRI, CT scans, and PET scans, into the current framework could potentially enhance the models' capability to extract comprehensive features and improve the accuracy of tumor detection and segmentation.

2. 3D Image Segmentation:

Extending the existing approach to accommodate three-dimensional (3D) volumetric data would allow for a more precise and comprehensive analysis of brain tumors, taking into account the spatial relationships within the entire volume.

3. Longitudinal Studies:

Conducting longitudinal studies to monitor tumor growth and treatment response over time would facilitate treatment planning and the evaluation of the effectiveness of therapeutic interventions.

4. Attention Mechanisms:

The exploration of attention-based mechanisms, such as self-attention or spatial attention, has the potential to improve segmentation accuracy by allowing the models to focus on relevant regions within the images, particularly for challenging cases.

5. Uncertainty Estimation:

The development of methods to estimate model uncertainty would offer valuable insights to clinicians and aid in understanding the reliability of the model's predictions.

Clinical Integration and Validation:Collaborating with medical professionals for real-world clinical validation is imperative to ensure the models' reliability and appropriateness for application in the medical field.

6. Low-Resource Settings:

Adapting the models for deployment in low-resource settings, where computational power and data availability are limited, would extend the reach of this technology to regions with restricted access to advanced medical facilities.

Acknowledgment

The making of the project "BRAIN TUMOR DETECTION AND SEGMENTATION USING DEEP LEARNING" involves the contribution of many people. We would like to convey our sincere thanks to Teesside University for giving us the opportunity to showcase our skills and providing us with the necessary resources. . We express deep gratitude to our project guide and mentor Suraj Verma for his constant motivation to think out of the box and immense contribution throughout to this project. . We also extend our heartfelt thanks to our families and well-wishers.

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