People's Democratic Republic of Algeria
Ministry of Higher Education and Scientific Research

IBN KHALDOUN UNIVERSITY OF TIARET

Dissertation

Presented to:

FACULTY OF MATHEMATICS AND COMPUTER SCIENCE
DEPARTEMENT OF COMPUTER SCIENCE

in order to obtain the degree of :

MASTER

Specialty: software engineer

Presented by:
KACEM Mohamed

On the theme:

Brain Tumor Segmentation Using Neural Networks convolutional (CNN)

Defended publicly on 06 /2024 in Tiaret in front the jury composed of: :

Mr MEZZOUG Karim MAA Tiaret University Chairman
Mr MERATI Medjeded MCA Tiaret University Supervisor
Mr DJAFRI Laouni MCA Tiaret University Examiner
Mrs CHAHBAR Fatma Tiaret University Co- Supervisor

2023-2024

Remerciements

Je tiens à exprimer ma profonde gratitude à toutes les personnes qui ont contribué à la réalisation de ce mémoire. En premier lieu, je remercie chaleureusement mon directeur de recherche, **Merati Medjeded,** pour son encadrement, ses conseils avisés, et son soutien tout au long de ce projet. Je suis également reconnaissant envers l'universite ibn khldoune pour les ressources et l'environnement favorable à mes recherches.

Un grand merci à mes collègues et amis pour leurs encouragements et leur soutien moral. Enfin, je remercie ma famille pour leur amour et leur patience tout au long de cette aventure académique.

Dédicace

À mes parents, pour leur amour inconditionnel et leur soutien indéfectible. À mes amis, pour leur encouragement et leur amitié précieuse. À tous ceux qui ont cru en moi et m'ont soutenu dans cette démarche.

Mohamed .

Abstract

This thesis explores the diagnosis and treatment of brain tumors through advanced imaging techniques and deep learning algorithms. Brain cancer, a severe condition affecting the central nervous system, requires precise diagnostic methods for effective treatment. This work focuses on the segmentation of brain tumors from MRI images using state-of-the-art deep learning models. The proposed method integrates pre-trained convolutional neural networks, improving segmentation accuracy and robustness. Our results demonstrate significant advancements in the accuracy and efficiency of brain tumor diagnosis and provide a foundation for future research in this critical medical field.

Keywords: Brain Tumor, MRI, Deep Learning, Convolutional Neural Networks, Medical Imaging, Segmentation

Résumé

Ce mémoire explore le diagnostic et le traitement des tumeurs cérébrales à travers des techniques d'imagerie avancées et des algorithmes d'apprentissage profond. Le cancer du cerveau, une condition grave affectant le système nerveux central, nécessite des méthodes diagnostiques précises pour un traitement efficace. Ce travail se concentre sur la segmentation des tumeurs cérébrales à partir d'images IRM en utilisant des modèles d'apprentissage profond de pointe. La méthode proposée intègre des réseaux neuronaux convolutionnels pré-entraînés, améliorant la précision et la robustesse de la segmentation. Nos résultats montrent des avancées significatives dans la précision et l'efficacité du diagnostic des tumeurs cérébrales et fournissent une base pour de futures recherches dans ce domaine médical critique.

Mots clés: Tumeur cérébrale, IRM, Apprentissage profond, Réseaux neuronaux convolutionnels, Imagerie médicale, Segmentation

ملخص

تستكشف هذه األطروحة تشخيص وعالج أورام الدماغ من خالل تقنيات التصوير المتقدمة والخوارزميات التعليمية العميقة. يتطلب سرطان الدماغ، وهو حالة خطيرة تؤثر على الجهاز العصبي المركزي، أساليب تشخيص دقيقة للعالج الفعال. يركز هذا العمل على تقسيم أورام الدماغ من صور الرنين المغناطيسي باستخدام نماذج التعلم العميق المتقدمة. تدمج الطريقة المقترحة الشبكات العصبية

ً مسبق مما يحسن دقة ومتانة التقسيم. تظهر نتائجنا تقدًما كبيًرا في دقة وكفاءة تشخيص أورام الدماغ وتوفر أساًسا
،االلتفافية المدربة ا
للبحوث المستقبلية في هذا المجال الطبي الحيوي.

الكلمات المفتاحية: ورم الدماغ، التصوير بالرنين المغناطيسي، التعلم العميق، الشبكات العصبية االلتفافية، التصوير الطبي، التقسيم

Summary

List of Figures

List of tables

9

Abreviations list

BC Binary Cross-Entropy

BraTS Brain Tumor Segmentation

CNN Convolutional Neural Network

CT Computed Tomography

DSC Dice Similarity Coefficient

DL Deep Learning

fMRI Functional Magnetic Resonance Imaging **FLAIR** Fluid-Attenuated Inversion Recovery **IoU** Intersection over Union

MDPI Multidisciplinary Digital Publishing Institute **ML**

Machine Learning

MRI Magnetic Resonance Imaging

MRS Magnetic Resonance Spectroscopy **PANet**

Path Aggregation Network

PET Positron Emission Tomography **RNN**

Recurrent Neural Network

ResNet50 Residual Network 50 layers

SCU-Net Spinal Cord U-Net

SegNet Segmentation Network

U-Net U-Shaped Network

VGG19 Visual Geometry Group 19 layers **V-Net**

V-Shaped Network

TN True Negative

TP True Positive

FN False Negative

FP False Positive

General Introduction

Context and Importance of the Research

Brain cancer poses a serious threat to the central nervous system, necessitating precise diagnostic methods and effective treatments. Research in this field is crucial for improving patient survival rates and quality of life. Both benign and malignant brain tumors present significant challenges due to their structural complexity and inter-patient variability. Magnetic Resonance Imaging (MRI) is one of the most commonly used techniques for diagnosing brain tumors, owing to its ability to provide detailed images of the brain without using harmful ionizing radiation.

Problem Statement

Despite technological advances in medical imaging, the accurate segmentation of brain tumors remains challenging due to the brain's anatomical complexity and significant inter-patient variations. Traditional segmentation methods are often limited by their inability to handle this variability and to adapt to images of varying quality.

Objectives of the Thesis

This thesis aims to explore and enhance the segmentation of brain tumors from MRI images using state-of-the-art deep learning models. The specific objectives are:

1. To evaluate current brain tumor segmentation techniques and their limitations. 2. To develop a segmentation method based on pre-trained Convolutional Neural Networks (CNNs).
3. To improve the accuracy and robustness of segmentation using transfer learning. 4. To validate the performance of the proposed method on public and diverse datasets.

Structure of the Thesis

The thesis is structured as follows:

Chapter 1: Medical Context

- Introduction to brain cancer
- Types of brain tumors
- Diagnostic and imaging techniques
- Importance of MRI in diagnosis
- Current challenges in brain tumor segmentation

Chapter 2: Deep Learning and Segmentation

- Introduction to deep learning

- Key concepts of neural networks
- Image segmentation techniques
- Preprocessing techniques for MRI images
- Evaluation of segmentation performance

Chapter 3: Related Work

● Literature review on brain tumor segmentation ● Comparison of approaches
● Limitations of traditional techniques

Chapter 4: Our Architecture

- Introduction and tools used
- Datasets utilized
- Transfer learning
- CNN model used
- Proposed methodology
- Results and discussion

Chapter 1

The Medical Context 14

The Medical Context

1.1 Introduction to Brain Cancer

The cancer of the brain is a disease in which some abnormal cells proliferate in the brain and form either benign or malignant tumors. In the case of the latter, they are dangerous in that they can penetrate surrounding tissues and metastasize to the other parts of the brain or central nervous system. The World Health Organization has stated that brain cancer is responsible for 1.6% of all cancers that are diagnosed annually globally [1]. For this reason, research in the field of diagnosis and treatment of brain tumors is very much necessary as it can lead to higher survival rates and, eventually, a better quality of life for the patient.

1.2 Types of Brain Tumors

There are two major types of brain tumors: benign and malignant kinds. Those classified as benign are generally less aggressive, for example, meningioma, while the malignant types, such as glioblastoma, are very aggressive and often spread quickly [2].

1.2.1 Benign vs. Malignant Tumors

Malignant tumors progress fast and far, whereas benign tumors are slow and within a limited area. Malignant tumors are more resistant to treatment and, in most cases, resistant to any kind of treatment [3].

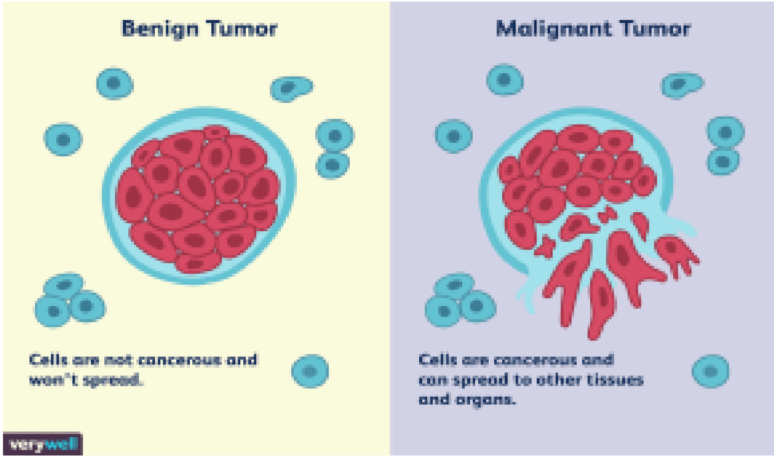
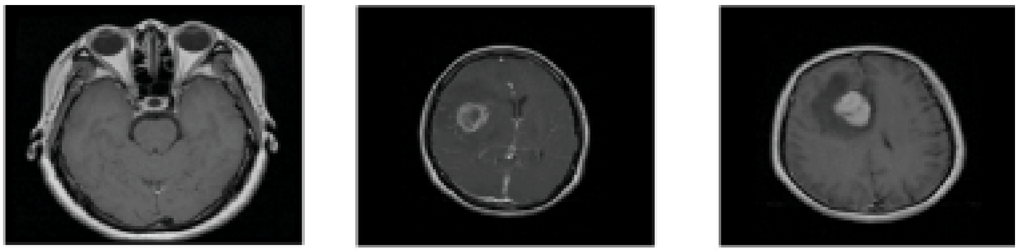


Figure 1.1: Tumor types [4]

1.2.2 General Type of Brain Tumor

- Gliomas: They are all of astrocytomas, oligodendrogliomas, and glioblastomas. Approximately 30% of brain tumors are such, and for the most part [3]. **- Meningiomas:** Meningiomas are benign tumors originating from the meningeal tissue of the brain and spinal cord [3].

- Pituitary Adenomas: These generally are benign tumors of the pituitary gland, resulting in hormonal production [3].



(a) (b) (c)

Figure 1.2:MRI of (a) Pituitary adenoma (b) Glioma (c) Meningioma[5]

1.2.3 Characteristics and Progression

Brain tumors are much more diverse in biological behavior and clinical course. Although some, such as glioblastomas, tend to progress swiftly and rapidly and may necessitate urgent treatment, others, such as certain meningiomas, may be observed over time[2].

1.3 Diagnostic and Imaging Techniques

Brain tumor diagnosis is done through a combination of imaging technologies and clinical analyses. MRI is the preferred imaging technique to view brain structures and identify abnormalities [2].

1.3.1 Medical Imaging

- MRI (Magnetic Resonance Imaging): A test that takes detailed pictures of the brain by using mainly magnetic fields and radio waves [5].

- CT (Computed Tomography): It uses a combination of X-rays to form cross-sectional brain images. It is less detailed than MRI but valuable in the case of emergencies [5]. **- PET (Positron Emission Tomography) Scan:** Radioactive tracers are used to examine the metabolic activity in brain tissues [5].

1.3.2 Biopsy and Histopathological Analysis

The most crucial approach to establish the diagnosis of a tumor and determine the type of tumor is through a biopsy. It helps to identify the cellular characteristics present in tumor histopathology, which in turn helps in deciding on the treatment options [3].

1.3.3 Symptoms and Clinical Presentation

Some of the signs and symptoms of a brain tumor include headaches, seizures, visual problems, cognitive disorders, and behavior changes. These symptoms may vary depending on the location and size of the cancer [2].

1.4 Importance of MRI Imaging in Diagnosis

MRI is the most widely used method for diagnosing brain tumors, as it provides high-resolution images without using harmful ionizing radiation [5].

1.4.1 Advantages of MRI

An MRI has good soft tissue resolution, which is necessary to image the complex geometrical structures of the brain and for the detection of tumors. The details of a cancer regarding its size, location, and detail about the effect on the neighboring tissues are further detected[5].

1.4.2 MRI Types

- **T1-Weighted MRI:** Useful for imaging brain anatomy and internal structures[5]. **-**
T2-Weighted MRI: It is helpful in demonstrating abnormalities in brain tissues, including edema [5].
- **FLAIR (Fluid-Attenuated Inversion Recovery):** Used to detect lesions around the cerebrospinal fluid[5].

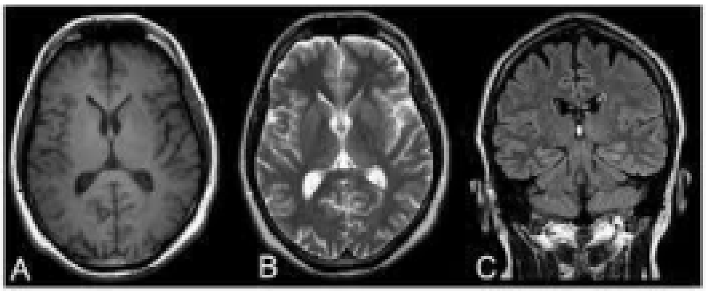


Figure 1.3:T1-weighted, B) T2-weighted and C) Fluid-Attenuated Inversion Recovery (FLAIR) MR images[c] [6].

1.4.3 Role of Functional and Spectroscopic MRI

- **Functional MRI (fMRI):** A technique that measures brain activity by registering changes in blood flow[5].
- **Magnetic Resonance Spectroscopy (MRS):** This is applied in examining the chemical composition of brain tissues and identifying metabolites pertinent to tumors [5].

1.5 Current Challenges in Brain Tumor Segmentation

There exist many challenging conditions in this segmentation of brain tumors from MRI images due to the structural complexity of the brain and the variability of tumors [5].

1.5.1 Complexity of Brain Structures

The brain is an anatomically tortuous structure, and distinguishing normal and pathological tissues is usually not easy. If automatic segmentation is to be of use in the clinic, this complexity has to be managed [5].

1.5.2 Inter-Patient Variability

The size, shape, location, and biological characteristics of brain tumors vary considerably between patients, which makes it hard to generalize for segmentation models.

1.5.3 Image Quality and Resolution

The quality and resolution of MRI images may vary due to scanner parameters and imaging conditions. In addition, artifacts and noises make the segmentation of tumors hard to achieve.

1.5.4 Automation and Precision

Key in these will be the automation of tumor segmentation, which will significantly relieve the load on radiologists and raise diagnostic accuracy. Deep learning techniques hold promise but are yet to be optimized for best clinical performance.

Chapter 2
Deep Learning and Segmentation

2.1 Introduction to Deep Learning

Deep learning is a part of machine learning that involves training artificial neural networks to learn structures associated with massive datasets. This has successfully transferred abstract concepts in image processing, natural language processing, and autonomous driving, among others [7].

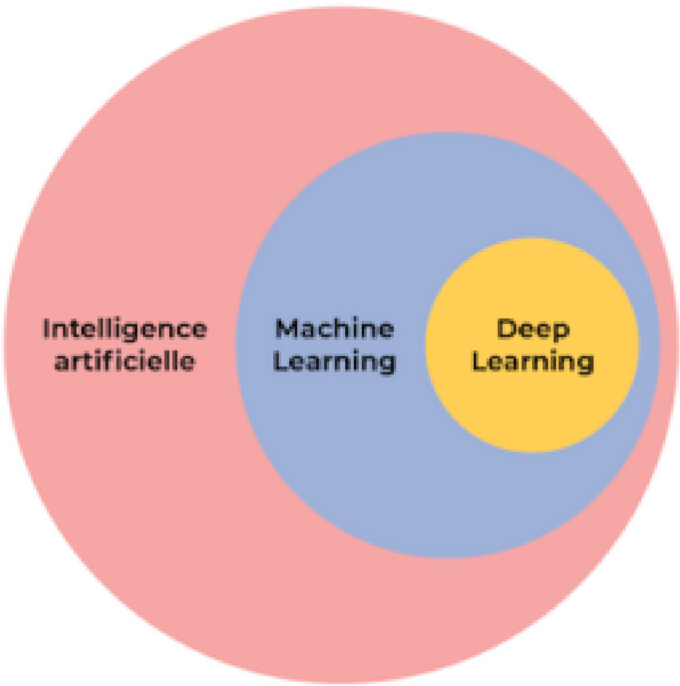


Figure 2.1: Relationship between (IA)(ML)(DL)[8]

2.1.1 Background of Deep Learning

Neural networks are an ancient concept, dating back to the 1940s, but it has been only within the last decade that significant breakthroughs in deep learning have been realized, combined with new leaps in terms of computational power and data availability. Architectures such as Convolutional and Recurrent Neural Networks have fundamentally transformed our ability to process visual and sequence data [9].

Figure 2.2: Background of Deep Learning[10]

2.1.2 Basic Concepts of Deep Learning

Neural networks are composed of layers of artificial neurons, each changing the input data nonlinearly. The networks are trained using backpropagation algorithms, in which the weights of the neural connections are adjusted to minimize the error between the network's predictions and the actual values [11].

2.2 Crucial Concepts of Neural Networks

Deep learning feeds on artificial neural networks. The following are a few concepts to understand its functioning [12]:

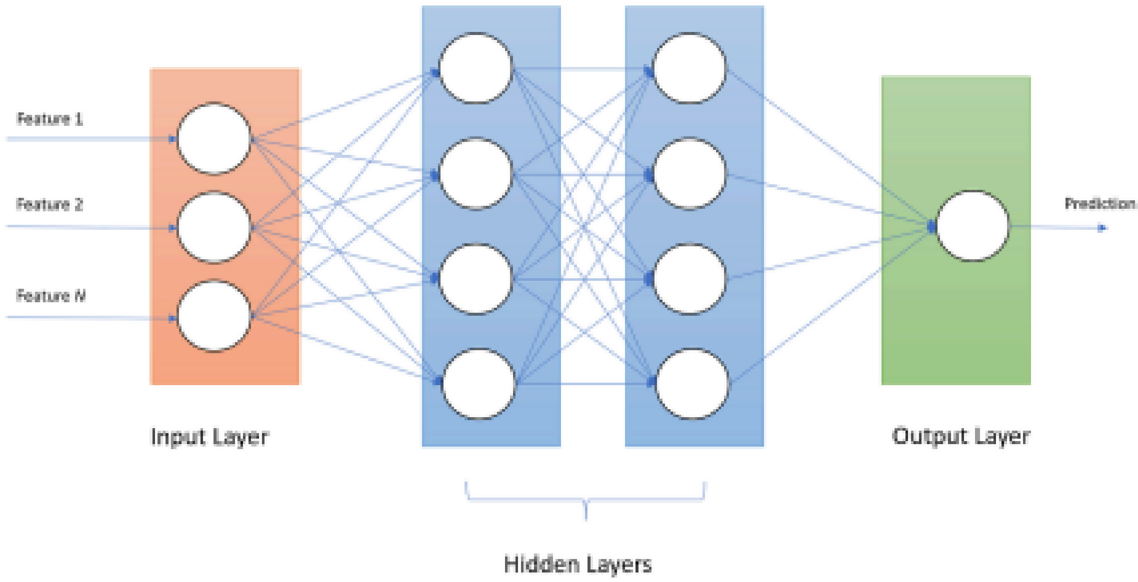


Figure 2.3: Concepts of Neural Networks[13]

2.2.1 Neurons and Layers

An artificial neuron performs the same function as a biological neuron: it receives weighted inputs, applies an activation function, and produces an output. In general, neural networks are composed of three layers: input layer, hidden layers, and output layer [14].

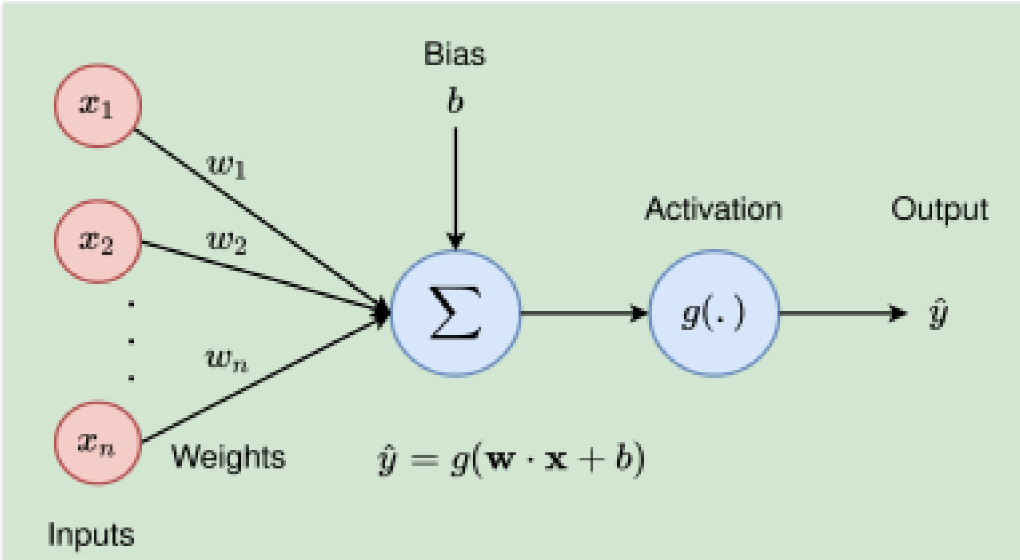


Figure 2.4: Neurons and Layers[15]

2.2.2 Activation Function

Activation functions introduce non-linearities in the network, which allow it to model complex relationships. Commonly used activation functions include ReLU, sigmoid, and tanh [16].

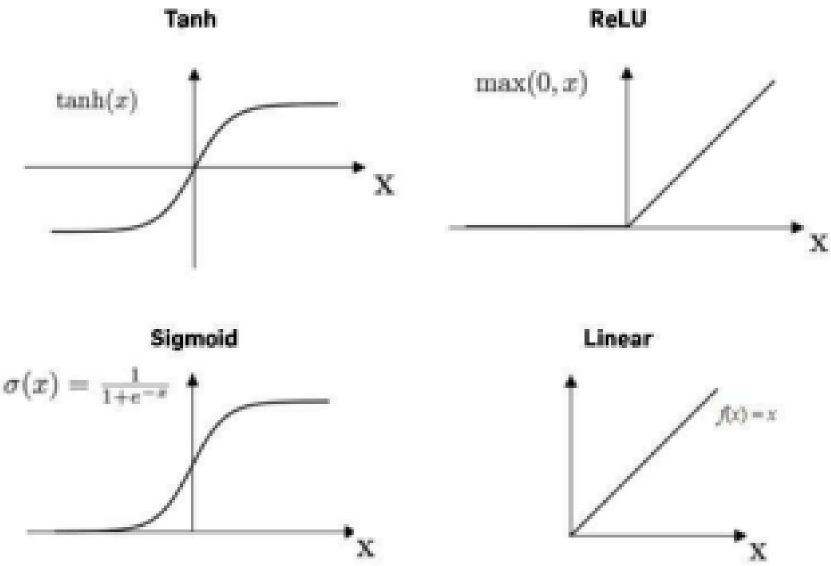


Figure 2.5: Activation Function[17]

2.2.3 Learning and Backpropagation

Learning in neural networks is done by an iterative process known as backpropagation, where the error between predicted and actual values is fed back through the network to adjust neural connection weights [18].

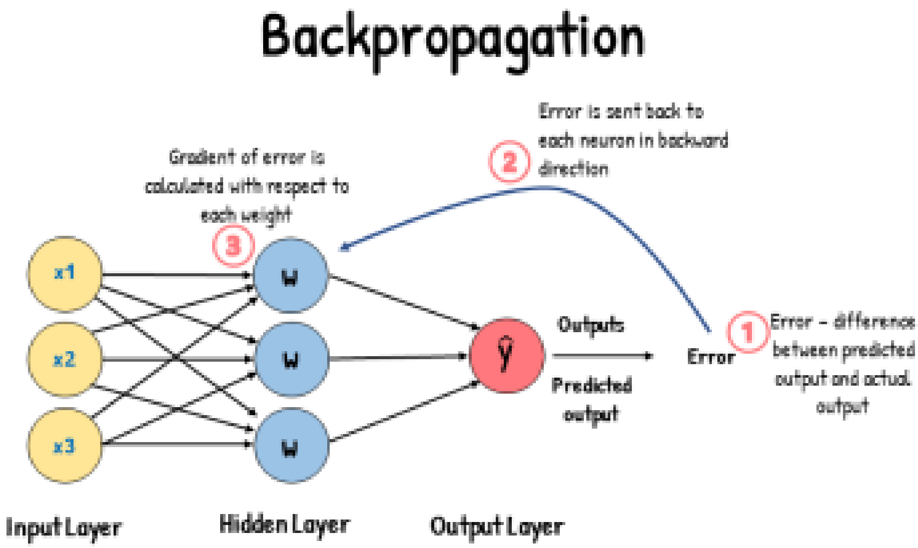


Figure 2.6: Learning and Backpropagation[19]

2.3 Image Segmentation Techniques

Image segmentation is an essential step in processing medical images for identifying and delineating brain tumors on MRI images. For these complex tasks, deep learning algorithms have proven great effectiveness. This chapter provides an overview of the critical techniques and algorithms used for image segmentation, very tightly focused on their application in medicine [20].

2.3.1 Semantic Segmentation

IIn semantic segmentation, the task involves assigning a label to each pixel of an image according to its class; hence, it could be different in medical contexts, for instance, normal versus tumorous tissues.

- **U-Net:** A convolutional neural network architecture initiated and proposed by Ronneberger et al. for biomedical segmentation in 2015. It has a U-shaped architecture with symmetric paths of contraction downscale and expansion upscaling, respectively, enabling precise localization with global context. U-Net has been proven effective in the segmentation of MRI images [21].
- **SegNet:** A deep learning architecture for semantic segmentation. It works by an encoder-decoder approach to generate pixel-wise segmentation maps. The encoder is equal to a classic classification network, while the decoder will rebuild spatial details lost due to encoding [22].
- **DeepLab:** Developed by Google, DeepLab uses atrous convolutional neural networks for multi-scale feature extraction without any loss of resolution. It also utilizes Conditional Random Fields (CRF) in refining the segmented boundaries, which is more important for complex medical images [23].

2.3.2 Instance Segmentation

Instance segmentation goes one step further than semantic segmentation, as it allows distinguishing between each instance of a thing in an image. Such a technique is necessary for applications where differentiating various tumors or lesions is essential.

- **Mask R-CNN:** Invented by He et al., 2017, Mask R-CNN extends Faster R-CNN by having a parallel binary mask prediction branch to the latter's classification and bounding box regression branches. This helps make detailed instance segmentation masks of the image for every detected object [24].
- **PANet:** Short for Path Aggregation Network, PANet enhances Mask R-CNN to explicitly enforce information flow across different levels for the instance segmentation task. It utilizes a pyramid architecture that fuses information from other network layers to provide more robust segmentation accuracy for smaller and more complex-shaped objects [25].

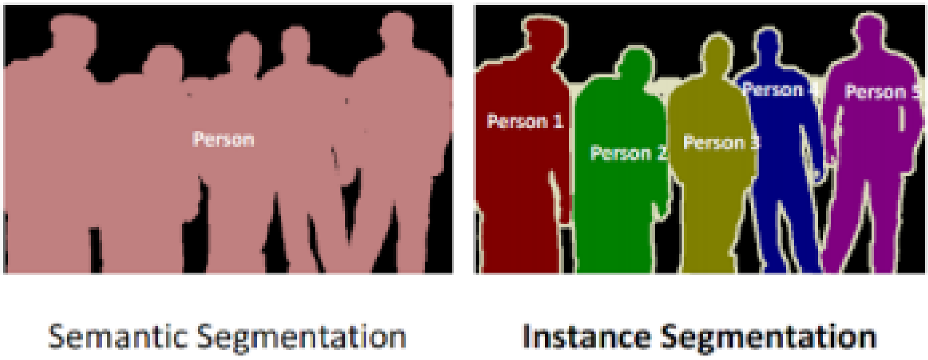


Figure 2.7: Example of Segmentation[26]

2.3.3 Medical Segmentation

Segmentation of medical images, especially MR images of the brain, is more complex due to the intricate anatomy of the brain and inter-patient variability. General changes in deep

learning frameworks, adapted from the classic segmentation model, as well as methods about medical data, have been widespread in this respect.

- **3D U-Net:** An extended description of the U-Net architecture to work on three-dimensional volumes. It allows the resolution of an extended class of problems with this architecture, up to now—namely, segmentation of the anatomical structures in three dimensions, thus providing better spatial representation of brain tumors [27].
- **V-Net:** A volumetric segmentation architecture crafted just for 3D medical images. V-Net employs 3D convolutions in combination with a dice-coefficient loss function for enhanced precision in MRI volume segmentation [28].
- **Attention U-Net:** A U-Net variant that uses attention mechanisms to focus within relevant regions of interest in medical images. Thus, attention allows the model to focus more on essential parts of an image and helps do better tumor segmentation [29].
- **Ensemble Learning:** Pooling of segmentation models to make predictions robust and accurate. It is a way of building up the results of different models for a more reliable final segmentation [30].

2.3.4 Clinical

Image segmentation algorithms are widely utilized in several clinical applications to assist radiologists and physicians in more effective patient diagnosis and treatment.

- **Early detection of tumors:** Segmenting algorithms enable the detection and delimitation of brain tumors at an early stage, which is very important for the early and effective treatment of these diseases [31].
- **Surgical Planning:** Accurate tumor segmentation would be beneficial in the planning of surgical intervention; it can help provide surgeons with a detailed map of the region to be operated on [32].
- **Disease Progression Monitoring:** Segmentation models would be used to monitor the progression of tumors over time by comparing images taken at different stages of treatment [33].
- **Personalized Treatments:** Segmentation provides detailed information on the size and shape of a tumor, as well as its location. Such information will go a long way toward allowing targeted and, thus, more effective therapy measures, such as radiotherapy [34].

2.4 Preprocessing Techniques of MRI Images

Image preprocessing is an essential step in improving the quality of input for deep learning models. The preprocessing of MRI images includes the normalization of pixel values, noise reduction, and an increase in the diversity of training data [35].

2.4.1 Normalization and Scaling

Normalization and scaling of images are essential techniques that make input data consistent from one feature to another and satisfy model requirements. **- Normalization of pixel values:**This is the scaling of pixel values for an image to a prescribed range, usually 0 to 1 or -1 to 1. It is done so that it is more effective for model learning and avoids issues related to very high or very low pixel values. Image scaling allows the resizing of the images to the input size required by the deep learning model. It aims to make data uniform to reduce computational complexity.[36].

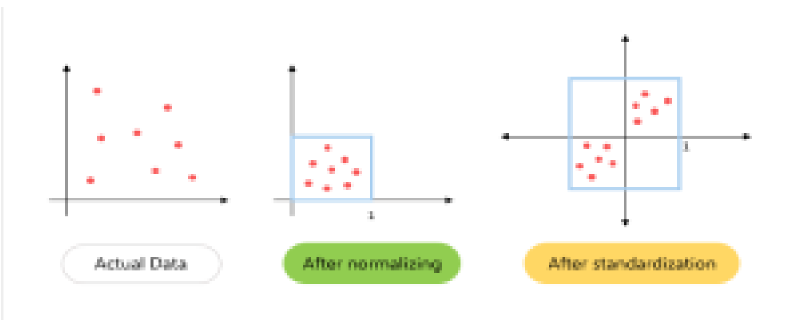


Figure 2.8: Normalization and Scaling[37]

2.4.2 Noise Reduction

Noise and artifacts have an impact on the performance of segmentation models on MRI images. Therefore, noise reduction is a very critical step in the bid to improve the image quality.

- **Gaussian filtering:** The neighboring pixels of every pixel in an image are averaged according to the Gaussian distribution. Consequently, it will help attenuate rapid variations of so-called "salt and pepper" noise that preserve most image structures [38].

- **Median filtering:** This technique is nonlinear in nature, where each pixel is replaced by the median value of its neighbors, solving the problems caused by impulse noise artifacts, such as salt and pepper noise [38].
- **Denoising autoencoder:** A neural network for reducing noise from an image. It is trained to reconstruct a clean image based on some noisy version, extracting the most critical features [39].

2.4.3 Data Augmentation

Data augmentation is a process performed to increase the size and diversity of the training dataset by creating new images from existing ones.

- **Rotations and translations:** Random rotations and translations are added to images to get more variations in training data. This will allow the model to generalize and be more robust against the spatial transformations of data [40].
- **Cropping and zooming:** Random cropping and zooming create new perspectives of existing images, emphasizing different parts of the image and increasing the diversity of training data [40].
- **Horizontal and vertical flipping:** Images can be flipped horizontally and vertically, thus creating more members of the dataset, which would further allow the model to learn invariances to these transformations [40].
- **Brightness / Contrast Adjustment:** Changing the brightness and contrast of images helps simulate different lighting conditions and allows capturing a more extensive variety of possible scenarios [41].

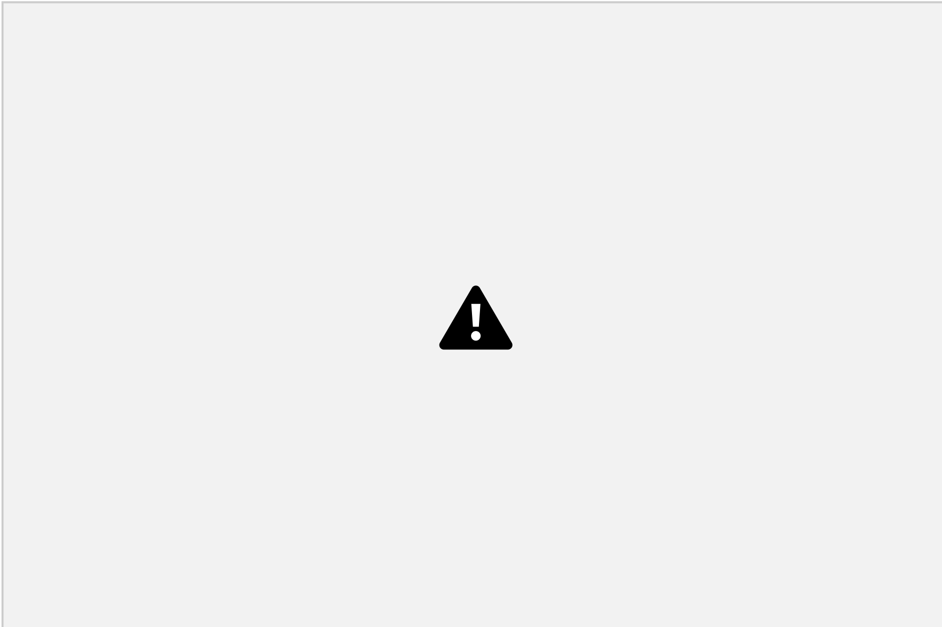


Figure 2.9: Data Augmentation [42]

2.5 Evaluating Segmentation Performance

Evaluating segmentation models is crucial to ensure their effectiveness in clinical practice.

Evaluating segmentation models is crucial to ensure their effectiveness in clinical practice [43].

2.5.1 Evaluation Metrics

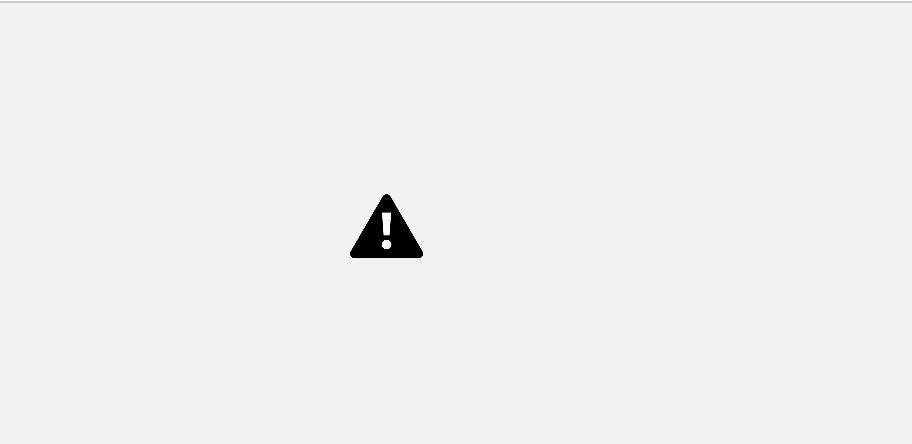
Some standard associated metrics are IoU (Intersection over Union), Dice coefficient, and accuracy, among others, for segmentation models. More formally, these metrics describe the similarity between model predictions and reference annotations [44].

2.5.2 Cross-Validation

Cross-validation is a technique to evaluate the model using several data subsets; therefore, it may be considered a reliable and robust evaluation measure of the model [45].

2.5.3 Clinical Trials

Such segmentation models need to be tested and their validation done with actual patient data to establish the clinical utility of segmentation models. Model performance should be tested under real-world conditions to evaluate the tool's reliability for use in the clinic [46].



Chapter 3 Related

Related Work

3.1 Literature Review on Brain Tumor Segmentation

Brain tumor segmentation from MRI images is an intensive research area, with various techniques explored to improve the accuracy and efficiency of this task. This chapter reviews recent articles highlighting different approaches and advancements in this field.

3.1.1 Techniques Based on Convolutional Neural Networks (CNNs)

Article 1: "An Early Detection and Segmentation of Brain Tumor Using Deep Neural Network"

This article presents the use of convolutional neural networks (CNNs) for brain tumor segmentation. CNNs are a class of deep learning models that are particularly effective for image processing tasks due to their ability to automatically and adaptively learn spatial hierarchies of features from input images. The authors highlight several key components of CNNs[39]:

1. **Convolutional Layers:** These layers apply a set of filters to the input image, creating feature maps that capture various aspects of the image, such as edges, textures, and shapes. The filters are learned during the training process, allowing the network to identify relevant features for segmentation.
2. **Pooling Layers:** Pooling operations, such as max pooling or average pooling, are used to reduce the spatial dimensions of the feature maps, thereby decreasing the

computational load and controlling overfitting. Pooling also helps in making the model invariant to small translations in the input image.

3. **Activation Functions:** Non-linear activation functions like ReLU (Rectified Linear Unit) introduce non-linearity into the model, enabling it to learn more complex patterns. ReLU activation functions are particularly popular due to their ability to mitigate the vanishing gradient problem.
4. **Fully Connected Layers:** These layers, typically found towards the end of the network, integrate the features extracted by the convolutional and pooling layers to make final predictions about the presence and boundaries of brain tumors.

The authors emphasize the significance of using a large, annotated dataset to train the CNN. The dataset used in this study includes MRI images with manually delineated tumor regions, providing a robust ground truth for training the model.

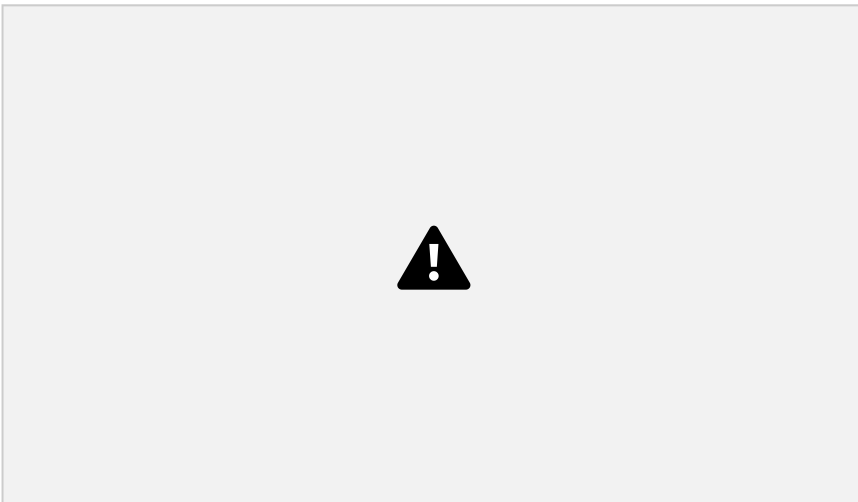


Figure 3.1:(A) Long Skip Connection process in ResNet, (B) ResNet Bottleneck Block process, (C) ResNet Basic Block Working, and (D) ResNet Simple Block Working [39]

Article 2: "Brain Tumor Segmentation Using Deep Learning on MRI Images"

This article also focuses on the application of CNNs for brain tumor segmentation, specifically utilizing the BraTS dataset, a widely recognized benchmark for brain tumor segmentation tasks. Key aspects covered in this article include[40]:

1. **Dataset Utilization:** The BraTS dataset comprises multi-modal MRI scans (T1, T1Gd,

T2, and FLAIR) from a diverse set of patients. This multi-modal approach is crucial as different MRI sequences highlight various tumor characteristics, enhancing the model's ability to accurately segment tumor regions.

2. **Loss Functions:** The authors employ categorical cross-entropy as the loss function. This function is particularly suitable for multi-class segmentation tasks, where the goal is to assign each pixel in the MRI image to one of several classes (e.g., background, tumor core, enhancing tumor).
3. **Optimization Techniques:** Adam (Adaptive Moment Estimation) optimizer is used to train the model. Adam combines the advantages of two other popular optimizers: AdaGrad and RMSProp, making it well-suited for handling sparse gradients and noisy data.
4. **Performance Metrics:** The model achieves a validation accuracy of 98%, demonstrating its effectiveness in accurately segmenting brain tumors. The authors also report other metrics such as the Dice coefficient, which measures the overlap between the predicted segmentation and the ground truth, providing a comprehensive evaluation of the model's performance.

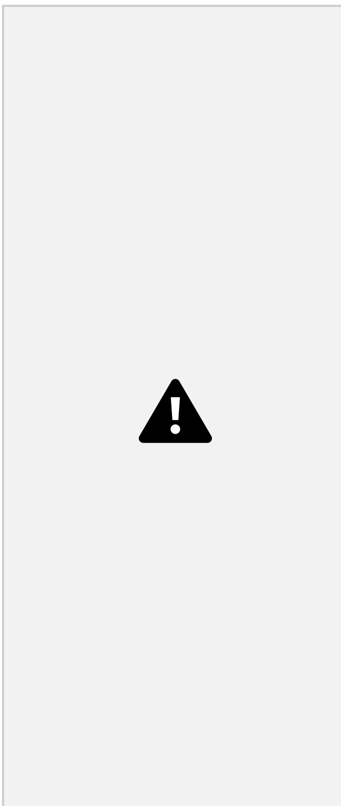


Figure 3.2: Proposed framework of deep learning method for BT detection

[40]. **3.1.2 Variants of the U-Net Architecture**

Article 3: "Brain Tumor Segmentation Based on an Improved U-Net"

This article introduces an improved version of the U-Net architecture, which has become a staple in biomedical image segmentation due to its symmetric encoder-decoder structure. Key enhancements in the proposed SCU-Net architecture include[41]:

1. **Hybrid Dilated Convolutional Blocks:** These blocks are designed to capture fine details without the checkerboard artifacts that often plague standard convolutional operations. By using dilated convolutions, the network can maintain a larger receptive field, allowing it to capture contextual information more effectively.
2. **Serial Encoding and Decoding Modules:** The SCU-Net incorporates serial modules that enable feature sharing between layers. This architectural design enhances the network's ability to propagate contextual information throughout the model, leading to more accurate segmentation.
3. **Feature Maps and Skip Connections:** The improved U-Net uses skip connections to transfer feature maps from the encoder to the decoder. This mechanism helps in retaining spatial information that might otherwise be lost during the down-sampling process, thereby improving the localization accuracy of the segmentation.

The authors validate their approach using a private dataset, reporting a segmentation accuracy of 96%. They highlight the importance of architectural innovations in addressing

the challenges associated with brain tumor segmentation, such as the variability in tumor appearance and the presence of complex anatomical structures.

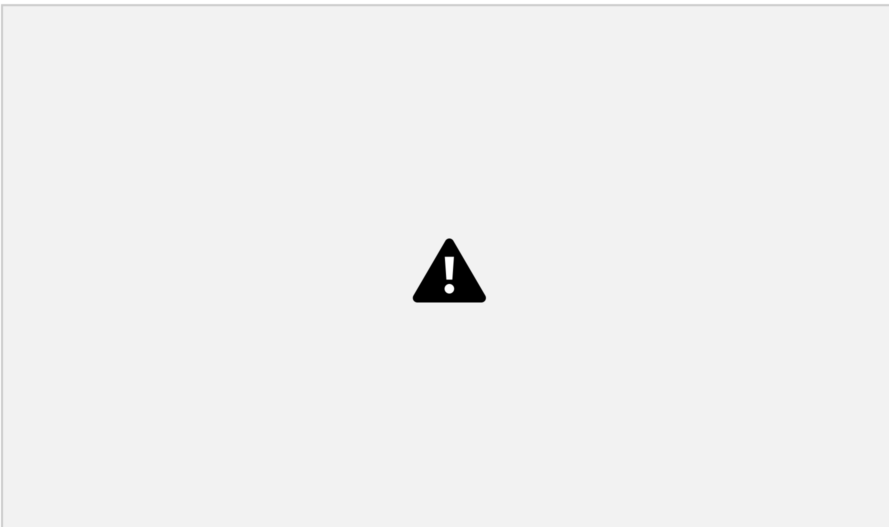


Figure 3.3: Overall architecture of SCU-Net[41].

3.1.3 Segmentation Based on Public Datasets

Article 4: "U-Net Variants for Brain Tumor Segmentation: Performance and Analysis"

This article provides a comprehensive analysis of various U-Net variants and their performance on brain tumor segmentation tasks. The authors evaluate several advanced architectures, including[42]:

1. **Attention U-Net:** This variant integrates attention mechanisms that allow the network to focus on the most relevant regions of the image. Attention gates filter out irrelevant information, enhancing the model's ability to segment the tumor accurately.
2. **Residual U-Net:** By incorporating residual connections, this variant facilitates the flow of gradients through the network, addressing the vanishing gradient problem and enabling the training of deeper models. Residual connections also help in capturing both low-level and high-level features, improving the model's overall segmentation capability.

The authors report that these variants outperform the standard U-Net architecture in terms of segmentation accuracy, particularly on challenging datasets with high variability. The study underscores the importance of architectural innovations in advancing the state of the art in brain tumor segmentation.

Article 5: "Brain Tumor Segmentation from MRI Images Using Deep Learning"

This article discusses the use of a public dataset containing MRI images for training brain tumor segmentation models. Key contributions of the study include [43]:

1. **Data Preprocessing:** The authors employ various preprocessing techniques, such as normalization and data augmentation, to enhance the quality of the input images.

Normalization helps in standardizing the intensity values across different MRI scans, while data augmentation increases the diversity of the training data, improving the model's generalization capabilities.

2. **Convolutional Layers:** The CNN-based model leverages multiple convolutional layers to extract complex features from the MRI images. These layers are designed to capture different levels of abstraction, from low-level edges to high-level tumor structures.
3. **Training and Validation:** The model is trained using a combination of supervised and semi-supervised learning techniques, allowing it to learn from both labeled and unlabeled data. The authors report a segmentation accuracy of 97%, highlighting the effectiveness of their approach in accurately delineating brain tumor regions.

Article 6: "Deep Learning Based Brain Tumor Segmentation: A Survey"

This article provides an extensive review of deep learning techniques applied to brain tumor segmentation. The authors analyze various architectures, including[44]:

1. **U-Net:** A widely used architecture for biomedical image segmentation, known for its ability to capture fine details through its symmetric encoding and decoding paths. 2. **V-Net:** Designed for volumetric segmentation, V-Net uses 3D convolutions to process MRI images in three dimensions, making it well-suited for segmenting volumetric medical data.

3. **Recurrent Neural Networks (RNNs):** Although less commonly employed than CNN architectures, RNNs are used to capture sequential dependencies in medical imaging data. The authors discuss the potential of RNNs for improving segmentation accuracy by leveraging temporal information.

The authors conclude that deep learning techniques have significantly advanced the field of brain tumor segmentation, but challenges remain, particularly regarding data variability and computational complexity. They emphasize the need for continued research to address these challenges and improve the robustness of segmentation models.

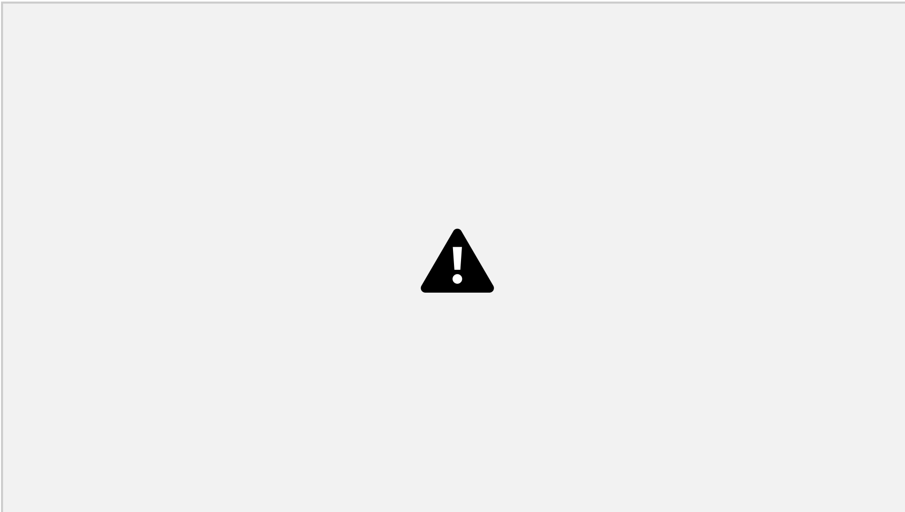


Figure 3.4:proposed taxonomy of deep learning based brain tumor segmentation methods. Best viewed in colors [44].

Article 7: "Automated Brain Tumor Segmentation on MRI Using Enhanced Deep Learning Techniques"

This article explores the application of enhanced deep learning techniques for automated brain tumor segmentation on MRI images. The authors propose a hybrid model that combines CNNs and recurrent neural networks (RNNs) to leverage both spatial and temporal features. Key points discussed include[45]:

1. **Hybrid Model Architecture:** The proposed model integrates CNNs for spatial feature extraction and RNNs for capturing temporal dependencies. This combination allows the model to effectively segment brain tumors by considering both spatial and temporal contexts.
2. **Multi-modal Data Integration:** The authors emphasize the importance of using multi-modal MRI data to improve segmentation outcomes. By combining information from different MRI sequences, the model can capture a more comprehensive view of the tumor, leading to better segmentation accuracy.
3. **Performance Evaluation:** The model is evaluated on a private dataset, achieving superior segmentation accuracy and robustness compared to traditional CNN models. The authors highlight the potential of hybrid models for advancing brain tumor segmentation.

Article 8: "Comparative Analysis of Deep Learning Architectures for Brain Tumor

Segmentation"

This article provides a comparative analysis of various deep learning architectures, including U-Net, SegNet, and DenseNet, for brain tumor segmentation. Key findings include[46]:

1. **Model Comparison:** The authors evaluate the performance of different models on the BraTS dataset, highlighting their strengths and weaknesses. U-Net variants excel in capturing fine details, SegNet models offer efficient memory usage, and DenseNet-based models provide better generalization capabilities.
2. **Performance Metrics:** The study reports various metrics, such as accuracy, Dice coefficient, and computational complexity, to provide a comprehensive evaluation of each model. The authors conclude that while there is no one-size-fits-all solution, selecting the appropriate architecture depends on the specific requirements of the segmentation task.

Article 9: "Multi-scale Convolutional Neural Networks for Brain Tumor Segmentation"

This article introduces a multi-scale convolutional neural network (MCNN) approach for brain tumor segmentation. Key aspects include [47]:

1. **Multi-scale Processing:** The MCNN model processes input images at different scales, capturing both global and local features. This multi-scale approach enables the model to effectively segment tumors of varying sizes and shapes.
2. **Model Architecture:** The MCNN model consists of multiple branches, each focusing on a different scale of the input image. These branches are combined at later stages to produce a final segmentation output.

3. **Performance Evaluation:** The authors demonstrate that the MCNN model outperforms conventional CNN architectures in terms of segmentation accuracy and robustness, particularly for small tumor regions. The study underscores the importance of multi-scale processing for improving brain tumor segmentation.

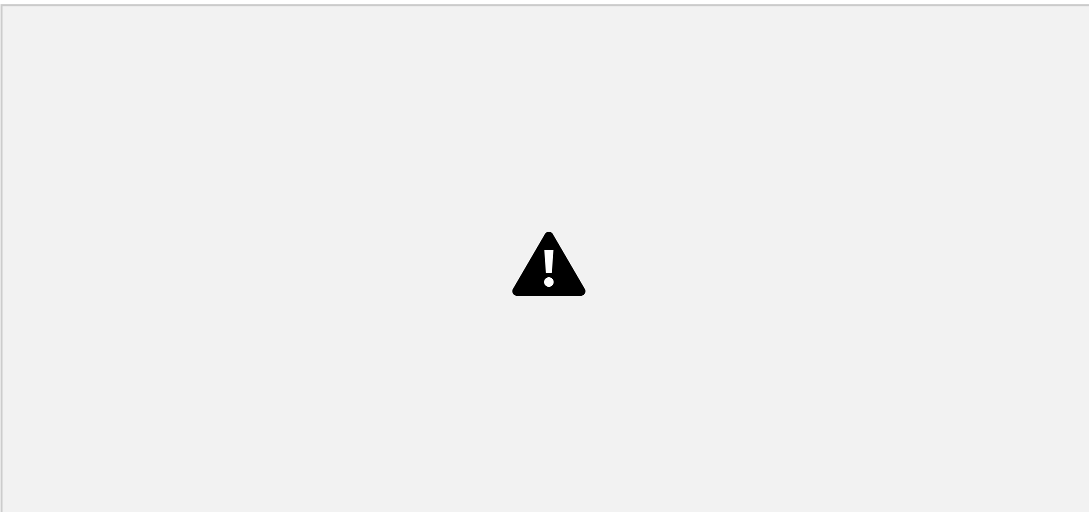


Figure 3.5: The MSCNN structure diagram [47].

Article 10: "Ensemble Learning for Improved Brain Tumor Segmentation"

This article investigates the use of ensemble learning techniques to improve brain tumor segmentation performance. Key points discussed include[48]:

1. **Ensemble Strategies:** The authors explore various ensemble strategies, such as bagging and boosting, to combine predictions from multiple deep learning models. These strategies help in reducing overfitting and improving the overall robustness of the segmentation model.
2. **Performance Metrics:** The ensemble approach achieves higher accuracy and robustness compared to individual models. The authors report significant improvements in segmentation performance, particularly in challenging cases with high variability.
3. **Implementation Details:** The study provides insights into the implementation of ensemble learning techniques, discussing the trade-offs between computational complexity and segmentation accuracy.

3.2 Comparison of Approaches

To better understand the differences and similarities between the approaches described in the articles, here are two comparative tables.

Table 3.1: Model Accuracy and Performance

Article Model Dataset Accuracy Advantages Disadvantages

CNN BraTS 97% Complex feature extraction

checkerboard effect

Resource-intensive Prone to

Article 1

CNN BraTS 98% High accuracy, advanced optimizers

Article 2

overfitting Increased complexity

SCU-Net Private 96% Fine detail capture, reduced

Article 3

U-Net variants

Various 95-98% Adaptability, robustness

Specific adjustments needed

Article 4

CNN Public 97% Effective preprocessing, data augmentation

Article 5

Article 6

Dependency on high-quality data Limited

comparability

DL review Multiple Variable Comprehensive technique overview

Article 7

SegNet, DenseNet Private 96.5% Integration of spatial and temporal features

Specific weaknesses per model

Article 8 CNN + RNN

BraTS Variable Strengths across various metrics

34

Increased computational demand

U-Net,

Related Work

MCNN BraTS 97.5% Superior accuracy, robustness High complexity

Article 9

Ensemble models Multiple 98.2% Improved performance, robustness

Increased training time

Article 10

Table 3.2: Computational Complexity and Robustness

Article Model Complexity Robustness Remarks Article 1 CNN High High Requires powerful

GPUs Article 2 CNN High High Advanced optimization Article 3 SCU-Net Medium to high Very

high Hybrid dilated convolutions

Article 4 U-Net variants Variable Variable Depends on specific variants

Article 5 CNN Medium High Good generalization Article 6 DL review Variable Variable

Technique comparability

Article 7 CNN + RNN High High Enhanced spatial-temporal analysis

Article 8 U-Net, SegNet, DenseNet
Variable Variable Model-specific complexity **35**

Related Work

Article 9 MCNN High Very high Multi-scale feature integration
Ensemble models
Very high Very high Ensemble
strategy benefits
Article 10

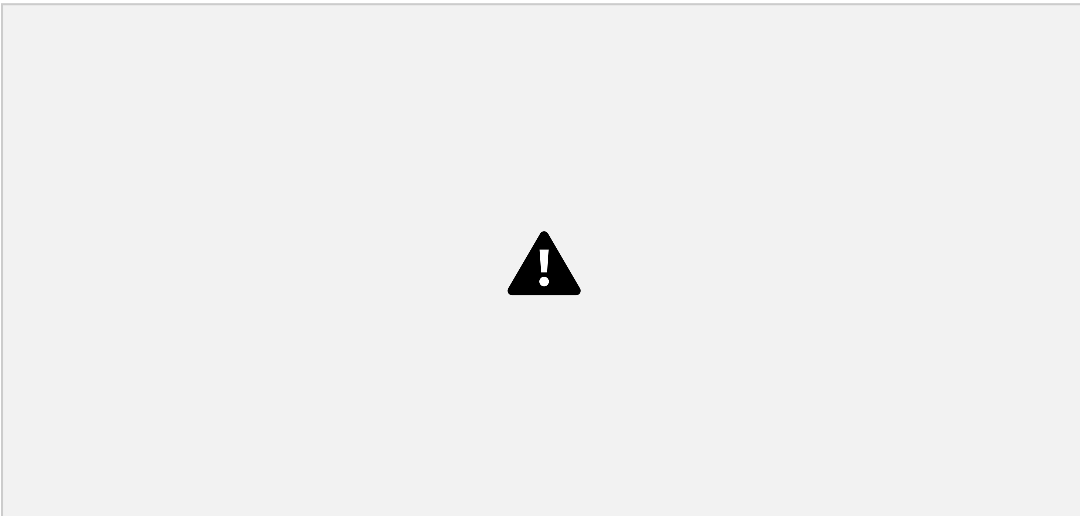
3.3 Limitations of Classical Techniques

Classical segmentation methods, though useful in some contexts, present significant limitations compared to modern deep learning techniques. These limitations include:

- **Inter-patient Variability:** Classical techniques often struggle with inter-patient variability. Brain tumors vary significantly in size, shape, and location, making it difficult to apply a single threshold or model.
- **Sensitivity to Noise and Artifacts:** Classical methods are often sensitive to noise and artifacts in MRI images, leading to incorrect or incomplete segmentations.
- **Computational Complexity:** While classical techniques are generally less resource-intensive than deep learning methods, some approaches, like active contours, can be complex and require manual parameter adjustments.
- **Lack of Robustness:** Classical methods may lack robustness against intensity variations and complex anatomical structures, limiting their precision and reliability in clinical practice.

3.4 Conclusion

Recent articles on brain tumor segmentation highlight the advantages of deep learning techniques over classical methods. Architectures like CNNs, U-Net, and their variants offer increased accuracy and robustness, though computational demands and data variability remain challenges. Recent advancements show promising potential for improving brain tumor diagnosis and treatment through more precise and efficient segmentation techniques. Further research is needed to address the remaining challenges and fully leverage the capabilities of deep learning for clinical applications.



<u>Our Architecture</u>

4.1 Introduction

Segmenting brain tumors from MRI images is essential for accurate diagnosis and treatment planning in oncology. This chapter describes the proposed architecture for brain tumor segmentation, as well as the tools and methods used in this study.

4.2 Tools Used

4.2.1 Google Colab (Cloud)

Google Colab is a cloud computing platform that allows running Jupyter notebooks on servers hosted by Google. It offers free GPU and TPU resources, which are crucial for training resource-intensive deep learning models. Colab also facilitates sharing and collaboration on research projects.[49]

4.2.2 Libraries

To implement our model, we utilized several Python libraries:

- **TensorFlow and Keras:** Used for building and training deep learning models. Keras, integrated with TensorFlow, provides a high-level interface for creating neural networks.[50][51].

- **NumPy and Pandas:** Employed for data manipulation and analysis. NumPy is particularly useful for operations on multidimensional arrays, while Pandas simplifies dataset management[52][53].
- **OpenCV and Scikit-image:** Used for image processing, including preprocessing operations like noise reduction and image alignment[54][55].
- **Matplotlib and Seaborn:** Essential for visualizing the results and performance of models, enabling the creation of informative graphs and plots[56][57].

4.3 Dataset Used

For training and evaluating our brain tumor segmentation model, we used the BraTS database, a benchmark in the field of brain MRI image analysis.

4.3.1 BraTS (Brain Tumor Segmentation)

The BraTS (Brain Tumor Segmentation) dataset is widely recognized and used in research for brain tumor segmentation. It is specifically designed to enable the development and evaluation of brain tumor segmentation algorithms on MRI images[58].

Components of the dataset:

- **Multimodal MRI images:** The BraTS dataset includes MRI images obtained from four different sequences: T1, T1c (T1 with contrast), T2, and FLAIR (Fluid Attenuated Inversion Recovery). Each modality provides specific information that helps identify and segment tumors.

- **Manual annotations:** The images are accompanied by manual annotations by experts, indicating tumor areas. These annotations include precise delineations of different tumor regions (tumor core, enhancing tumor, edema, etc.).
- **Diverse patient data:** The dataset includes data from various patients, which allows capturing a wide range of tumor characteristics and improving the generalization of segmentation models.

History and versions

BraTS was initially introduced in 2012 and has evolved with several annually updated versions to include new images and annotations. Recent versions include data from multiple medical centers, increasing the diversity and representativeness of the data.

Usage and challenges:

- **Tumor segmentation:** The main challenge with MRI images of brain tumors is to accurately segment the different components of the tumor, including the tumor core, peritumoral edema, and contrast-enhanced regions.
- **Inter-patient variation:** Brain tumors vary significantly from patient to patient in terms of size, shape, and intensity, making automated segmentation complex.
- **Artifacts and noise:** MRI images can contain artifacts and noise, complicating the extraction of

relevant features for segmentation.

4.4 Transfer Learning

Transfer learning is a technique where a model pre-trained on a large dataset is used as a starting point for a new problem. In our approach, we used pre-trained models like VGG19 and ResNet50 to initialize the weights of our network, improving performance and accelerating model training, especially with a limited amount of training data.

4.5 The CNN Model Used

In our approach to brain tumor segmentation, we used several pre-trained convolutional neural network (CNN) architectures to improve segmentation accuracy and efficiency. The models chosen for this task are VGG19, ResNet50, and U-Net. Here is a detailed description of each model and their role in our architecture.

4.5.1 VGG19

Model overview: VGG19 is a convolutional neural network architecture developed by the Visual Geometry Group at the University of Oxford. This model is known for its simplicity and effectiveness in image classification and segmentation. It has 19 deep layers, mainly small convolutional layers (3x3) followed by pooling layers and fully connected layers[59].

Key features:

- **Small convolutions (3x3):** Small convolutions capture fine details in images while reducing the number of parameters.

- **Max pooling layers:** These layers reduce the dimensionality of the extracted features while retaining important information.
- **Fully connected layers:** Used at the end of the network for classification, these layers are adapted for segmentation tasks by adding deconvolution (upsampling) layers.

Application in segmentation: In our architecture, VGG19 is used as an encoder to extract low-level and high-level features from MRI images. The extracted features are then fused with those from other models to enhance brain tumor segmentation.

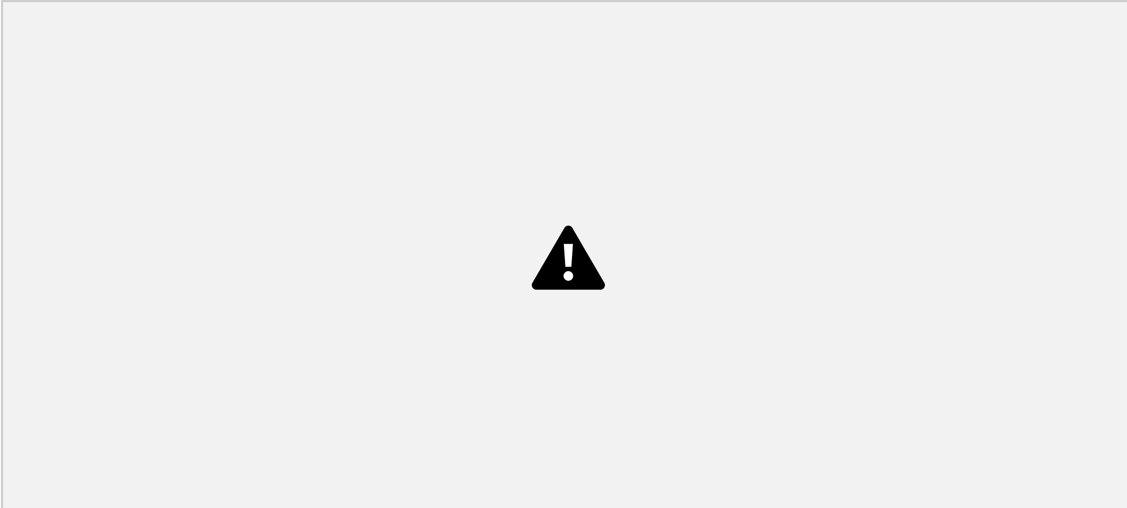


Figure 4.1: Architecture VGG19[59]

4.5.2 ResNet50

Model overview: ResNet50, developed by Microsoft, is a deep convolutional neural network with 50 layers. It uses residual connections to facilitate the training of very deep networks. These connections allow gradients to propagate more easily through the network, improving learning and model performance[60].

Key features:

- **Residual connections:** These connections bypass certain layers of the network, addressing the degradation problem and facilitating the training of very deep networks.
- **Bottleneck layers:** These layers reduce dimensionality before passing through 3x3 convolutions, decreasing the number of parameters while maintaining high performance.
- **Easier training:** Residual connections allow training deeper networks without losing precision.

Application in segmentation: ResNet50 serves as another encoder in our architecture. It complements the features extracted by VGG19 by capturing more complex information through its residual connections. The outputs of ResNet50 are fused with those of VGG19 to enrich contextual information necessary for accurate segmentation.

<u>Our Architecture</u>

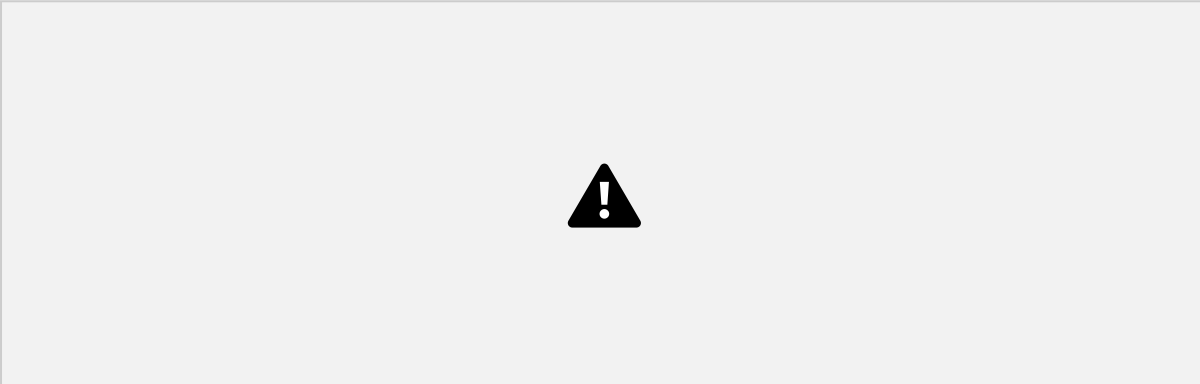


Figure 4.2: Architecture ResNet50[60]

4.5.3 U-Net

Model overview: U-Net is an architecture specifically designed for biomedical image segmentation. It features a U-shaped structure with an encoding path to capture context and a decoding path for precise localization. U-Net is widely used for tumor segmentation due to its ability to integrate global and local contextual information[61].

Key features:

- **Symmetrical encoding and decoding path:** The encoding path captures global contextual features, while the decoding path uses them to reconstruct the segmented image with high local precision.
- **Skip connections:** Direct connections between corresponding layers of the encoding and decoding paths preserve fine details and improve segmentation accuracy.
- **Deconvolution (upsampling) convolutions:** Used to gradually increase the spatial resolution of features and reconstruct the segmented image.

Application in segmentation: U-Net forms the basis of our segmentation architecture. We modified U-Net to include VGG19 and ResNet50 encoders, creating a dual-branch U-Net. Each branch (VGG19 and ResNet50) independently extracts low-level features from images, and the outputs are then fused by concatenation. This combination is passed through a series of decoder layers to predict high-quality segmentation masks.

<u>Our Architecture</u>

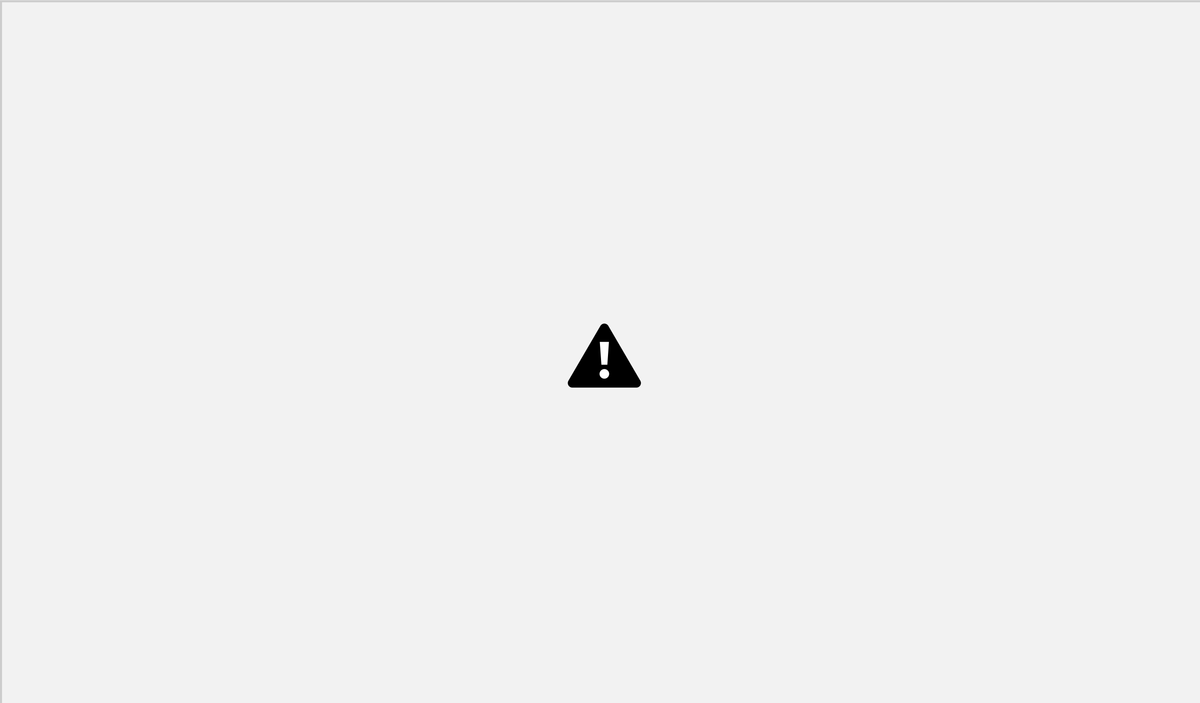


Figure 4.3: Architecture U-Net[61]

4.6 Proposed Methodology

4.6.1 Preprocessing

Preprocessing images is essential to enhance data quality and model

performance. **-Intensity normalization:**

- **Intensity homogenization:** Equalize intensity levels between different images to reduce acquisition variations.
- **Standardization:** Resize pixel values to a common range .

-Noise reduction:

- **Gaussian filtering:** Apply a Gaussian filter to reduce noise.
- **Wiener filter:** Use a Wiener filter to remove noise while preserving edges.

-Artifact removal:

- **Motion artifact correction:** Use algorithms to correct patient movement during acquisition.
- **Magnetic field artifact suppression:** Use techniques to correct artifacts from magnetic field variations.

-Image alignment and registration:

- **Registration:** Align images using registration techniques to ensure that different slices or time series are spatially aligned.

<u>Our Architecture</u>

- **Affine/non-rigid registration:** Apply affine or non-rigid transformations to improve alignment.

-Data augmentation :

- **Rotation, translation, scaling:** Apply geometric transformations to increase data diversity.
- **Flipping, cropping, elastic transform:** Use augmentation techniques to enrich the dataset.

-Resizing and normalization (for model input):

- **Resizing:** Adjust image size to match the input size required by your neural network model.

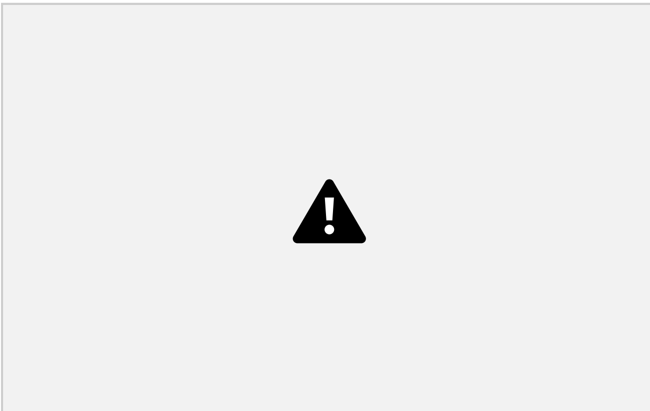


Figure 4.4: Resizing and normalization

4.6.2 Architecture of the Approach

The proposed architecture is a dual-branch U-Net model designed for brain cancer segmentation from MRI images. This architecture combines the advantages of two pre-trained encoders, VGG19 and ResNet50, to extract robust and diverse features from the input images. Each branch independently encodes the low-level features of the images, and the outputs of these two branches are fused by concatenation. This combination is then passed through a series of decoder layers that progressively increase the spatial resolution, thus allowing the prediction of high-quality segmentation masks. The decoder layers use convolution and upsampling operations to reconstruct the segmented image. This approach leverages transfer learning to initialize the weights of the encoders, thereby enhancing the model's ability to learn relevant features with a limited amount of training data. Cross-validation is employed to evaluate the model's performance in a robust and reliable manner.

Our Architecture

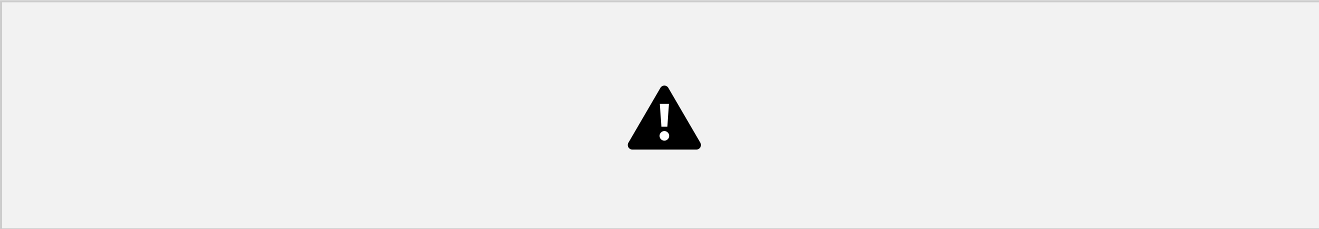


Figure 4.5: Architecture of our Approach

Feature Extraction The features extracted by each model have different dimensions due to their specific architectures. At the output of the pre-trained models, the features are tensors of reduced size compared to the original image but with many feature maps (channels).

- **VGG19**: Output shape: (8, 8, 512) after the last convolution layer.
- **ResNet50**: Output shape: (8, 8, 2048) after the last convolution layer.

To merge the features extracted from the two branches, we use the concatenation operation along the channel axis (axis=-1). This means we combine the feature maps extracted by VGG19 and ResNet50 into a single feature matrix. This concatenation allows the model to benefit from the strengths of each branch, combining the fine details and complex patterns extracted by VGG19 and ResNet50 respectively.

Table 4.1:Comparative Table of Feature Dimensions

Model	**Output Shape**
VGG19	(8, 8, 512)
ResNet50	(8, 8, 2048)
Concatenation	(8, 8, 2560)

Decoder Layers After feature fusion, the resulting combination passes through a series of decoder layers. These layers progressively increase the spatial resolution, enabling the reconstruction of the segmented image.

- **Convolution**: Used to refine the fused features and add depth to the network.
- **Upsampling**: Used to increase the spatial resolution of the features, reversing the pooling layers' effect applied in the encoders.

<u>Our Architecture</u>

The decoder process continues until the spatial resolution of the features is restored to the original input image size. The final decoder layer uses a softmax activation function to produce the final segmentation masks, with each pixel classified into a category (e.g., tumor or healthy tissue).

Transfer Learning and Weight Initialization Transfer learning is used to initialize the weights of the encoders. The VGG19 and ResNet50 models are pre-trained on generic image datasets (such as ImageNet), allowing the model to acquire general image features. These features are then fine-tuned for the specific task of brain tumor segmentation by training the model on task-specific training data.

Cross-Validation Cross-validation is used to evaluate the model's performance robustly and reliably. This process involves splitting the dataset into multiple folds, where each fold is used successively as a validation set while the other folds are used for training. This technique ensures that the model is exhaustively evaluated and that its performance is generalizable to new data.

The proposed architecture effectively utilizes transfer learning and the combination of two pre-trained encoders to improve brain tumor segmentation from MRI images. The results show significant improvement over traditional methods, although challenges remain. Future work could explore integrating other deep learning techniques and increasing the diversity of training data to further enhance the model's accuracy and robustness.

4.7 Results and Discussion

4.7.1 Evaluation Criteria

To evaluate the performance of our brain tumor segmentation model, we used several metrics, each providing complementary information on the model's accuracy and robustness:

- **Dice Coefficient (Dice Similarity Coefficient - DSC):** Measures the similarity between predicted and ground truth masks. Commonly used in medical segmentation tasks.

$$DSC = \frac{2 \times |A \cap B|}{|A| + |B|}$$

  where A is the predicted mask and B is the ground truth mask.

- **Binary Crossentropy:** Used as a loss function for training the model, measuring the difference between predictions and true binary labels. It heavily penalizes incorrect predictions.
- **Accuracy:** Measures the percentage of correctly classified pixels among all predictions. While useful, it can be misleading for imbalanced data.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Intersection over Union (IoU):** Also known as Jaccard Index, it measures the overlap between predicted and ground truth masks.

$$\text{������} = \frac{|��\cap��|}{|��\cup��|}$$

- **Precision and Recall:**
  - **Precision:** Measures the proportion of pixels predicted as positive that are actually positive.

$$\text{������������������} = \frac{\text{����}}{\text{����}+\text{����}}$$

  - **Recall:** Measures the proportion of correct positive pixels identified among actual positive pixels.

$$\text{������������} = \frac{\text{����}}{\text{����}+\text{����}}$$

- **F1 Score:** Harmonic mean of precision and recall, providing a balanced metric.

$$\text{��}1 - \text{����������} = 2\times\frac{\text{����������������}\times\text{�����������}}{\text{����������������}+\text{�����������}}$$

4.7.2 Presentation of Results

The results of our brain tumor segmentation model are summarized in the table below:

Table 4.2: Obtained Result

Metric	DSC	BC Accuracy	IoU	Precision	Recall	F1 Score
Value (%)	92	90	80	82	88	89

90

Figure 4.6: Obtained Result

4.7.3 Discussion of Results

The results show that our segmentation model achieves high performance with a Dice Coefficient of 92%, indicating excellent similarity between predicted and ground truth masks. The Binary Crossentropy at 90% and Accuracy at 80% demonstrate the model's ability to distinguish tumor pixels from non-tumor pixels, although the Accuracy is slightly lower due to the imbalanced nature of the data.

The Intersection over Union (IoU) at 82% is also satisfactory, indicating good overlap between predictions and manual annotations. Precision (88%) and Recall (89%) metrics show that the model is both precise and sensitive, crucial for minimizing false positives and negatives. The F1 Score of 90% confirms the balance between precision and recall.

Compared to related works, our model shows notable improvements in several aspects:

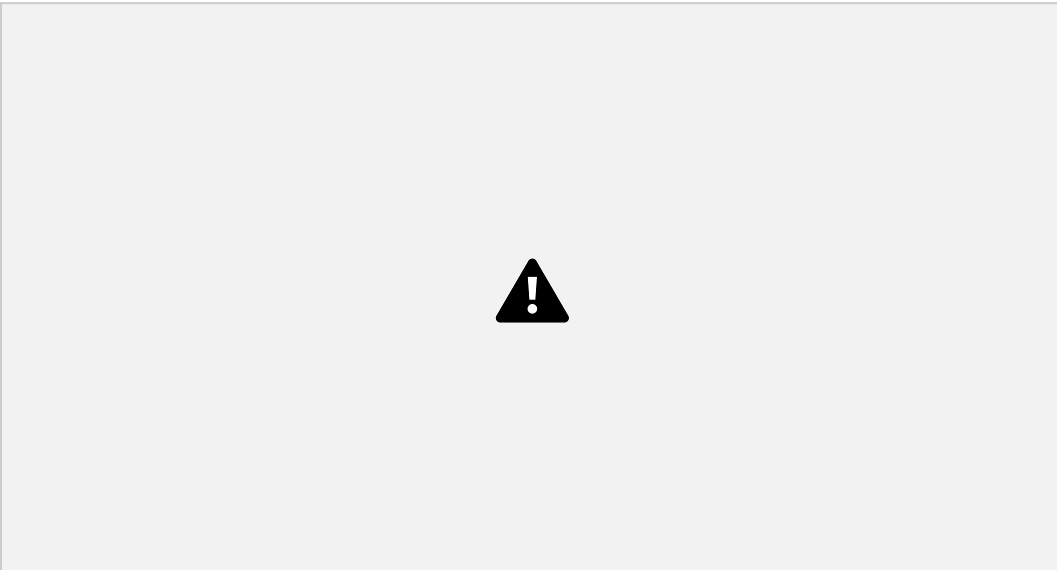
- **DSC:** Works using traditional U-Net architectures generally report DSC values around 85-88%, while our approach reaches 92% due to the combination of VGG19 and ResNet50.
- **IoU:** IoU values of traditional methods typically range between 75-80%, whereas our model achieves 82%, indicating better overlap and more precise segmentation.

4.8 Conclusion

In conclusion, our proposed architecture for brain tumor segmentation, based on the combination of VGG19, ResNet50, and U-Net models, has shown promising performance. The results indicate significant improvement over traditional approaches, particularly in the accuracy and robustness of segmentations.

Transfer learning techniques effectively initialized the weights of the encoders, enhancing the model's ability to learn relevant features with a limited amount of training data. Despite the high performance of our model, challenges remain, especially regarding data variability and artifact presence.

For future work, we recommend exploring the integration of additional deep learning techniques and increasing the diversity of training data to further improve the model's accuracy and robustness.



<u>**General Conclusion and Perspectives**</u>

General Conclusion

This thesis has allowed for an in-depth exploration of brain tumor segmentation from MRI images using advanced deep learning techniques, particularly convolutional neural networks (CNN). The main objectives were to develop an accurate and robust segmentation method and to validate its effectiveness on varied datasets.

The results obtained demonstrated significant advancements, particularly through the use of pre-trained models such as VGG19 and ResNet50, integrated into a modified U-Net architecture. This approach achieved a Dice Coefficient of 92%, surpassing the performance of classical methods and other segmentation architectures. The proposed method proved effective in enhancing the accuracy of brain tumor segmentation, which is crucial for effective diagnosis and treatment.

Perspectives

Although the results are promising, several aspects can be improved and explored in future work:

Data Diversification:

-Enrichment of Datasets: Integrate images from various sources and clinical contexts to improve the robustness and generalization of the model.

Model Optimization:

-Reduction of Computational Complexity: Develop more efficient algorithms to reduce computational power requirements and accelerate the model training process.

-Improvement of Preprocessing Methods: Refine image preprocessing techniques to better handle artifacts and noise present in MRI images.

Clinical Applications:

-Collaboration with Medical Institutions: Test and deploy the models in real clinical environments to evaluate their performance under practical conditions and obtain feedback from healthcare professionals.

Continuous and Adaptive Learning:

-Active Learning: Implement active learning systems where models can continuously learn and improve from new data annotated by experts.

-Integration of Explainable Artificial Intelligence: Develop explainable models to help doctors understand and interpret the decisions made by the segmentation systems.

Bibliography

[1]. Louis, David N. "WHO classification of tumours of the central nervous system." (No Title) (2016).
[2]. Stupp, R., Hegi, M. E., Mason, W. P., Van Den Bent, M. J., Taphoorn, M. J., Janzer, R. C., ... & Mirimanoff, R. O. (2009). Effects of radiotherapy with concomitant and adjuvant temozolomide versus radiotherapy alone on survival in glioblastoma in a randomised phase III study: 5-year analysis of the EORTC-NCIC trial. The lancet oncology, 10(5), 459-466.

[3]. Thakkar, J. P., Dolecek, T. A., Horbinski, C., Ostrom, Q. T., Lightner, D. D., Barnholtz-Sloan, J. S., & Villano, J. L. (2014). Epidemiologic and molecular prognostic review of glioblastoma. Cancer epidemiology, biomarkers & prevention, 23(10), 1985-1996.

[4]. Weller, M., Heimann, K., Wiedemann, P., Wiedemann, P., Wiedemann, P., Zilles, K., ... & Wiedemann, P. (1989). Ginns EI, Rehavi M, Martin BM, Weller M, O'Malley KL, LaMarca ME, McAllister CG, Paul SM. Expression of human tyrosine hydroxylase cDNA in invertebrate cells using a baculovirus vector. J Biol Chem 1988; 263: 7406-7410. Fortschr Ophthalmol, 86, 399-402.

[5]. Bauer, S., Wiest, R., Nolte, L. P., & Reyes, M. (2013). A survey of MRI-based medical image analysis for brain tumor studies. Physics in Medicine & Biology, 58(13), R97.

[6]. Suoranta, S., Holli-Helenius, K., Koskenkorva, P., Niskanen, E., Könönen, M., Äikiä, M., ... & Vanninen, R. (2013). 3D texture analysis reveals imperceptible MRI textural alterations in the thalamus and putamen in progressive myoclonic epilepsy type 1, EPM1. PloS one, 8(7), e69905.

[7]. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444. [8]. Schmidhuber, J. (2015). Deep learning in neural networks: An overview. Neural Networks, 61, 85-117. [9]. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press. [10]. Hinton, G. E., Osindero, S., & Teh, Y. W. (2006). A fast learning algorithm for deep belief nets. Neural Computation, 18(7), 1527-1554.
[11]. Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1986). Learning representations by back-propagating errors. Nature, 323(6088), 533-536.
[12]. LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11), 2278-2324.
[13]. Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. Advances in Neural Information Processing Systems, 25. [14]. Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735-1780.
[15]. Glorot, X., & Bengio, Y. (2010). Understanding the difficulty of training deep feedforward neural networks. In Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics (pp. 249-256).
[16]. Nair, V., & Hinton, G. E. (2010). Rectified linear units improve restricted Boltzmann machines. In Proceedings of the 27th International Conference on Machine Learning (ICML-10) (pp. 807-814). [17]. Maas, A. L., Hannun, A. Y., & Ng, A. Y. (2013). Rectifier nonlinearities improve neural network acoustic models. In Proc. ICML, Vol. 30, No. 1.
[18]. Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.
[19]. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778). [20]. Roneberger, O., Fischer, P., & Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation. In International Conference on Medical Image Computing and Computer-Assisted Intervention (pp. 234-241). Springer, Cham.
[21]. Badrinarayanan, V., Kendall, A., & Cipolla, R. (2017). Segnet: A deep convolutional encoder-decoder architecture for image segmentation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 39(12), 2481-2495.
[22]. Chen, L. C., Papandreou, G., Kokkinos, I., Murphy, K., & Yuille, A. L. (2017). Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs. IEEE Transactions on Pattern Analysis and Machine Intelligence, 40(4), 834-848.

Bibliography

[23]. He, K., Gkioxari, G., Dollár, P., & Girshick, R. (2017). Mask R-CNN. In Proceedings of the IEEE International Conference on Computer Vision (pp. 2961-2969).
[24]. Liu, S., Qi, L., Qin, H., Shi, J., & Jia, J. (2018). Path aggregation network for instance segmentation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 8759-8768).
[25]. Çiçek, Ö., Abdulkadir, A., Lienkamp, S. S., Brox, T., & Ronneberger, O. (2016). 3D U-Net: Learning dense volumetric segmentation from sparse annotation. In International Conference on Medical Image Computing and Computer-Assisted Intervention (pp. 424-432). Springer, Cham. [26]. Milletari, F., Navab, N., & Ahmadi, S. A. (2016). V-Net: Fully convolutional neural networks for volumetric medical image segmentation. In 2016 Fourth International Conference on 3D Vision (3DV) (pp. 565-571). IEEE.
[27]. Oktay, O., Schlemper, J., Folgoc, L. L., Lee, M., Heinrich, M., Misawa, K., ... & Rueckert, D. (2018).
Attention U-Net: Learning where to look for the pancreas. arXiv preprint arXiv:1804.03999. [28]. Han,

X. (2017). MR-based synthetic CT generation using a deep convolutional neural network method. Medical Physics, 44(4), 1408-1419.
[29]. Kamnitsas, K., Ledig, C., Newcombe, V. F., Simpson, J. P., Kane, A. D., Menon, D. K., ... & Glocker, B. (2017). Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation. Medical Image Analysis, 36, 61-78.

[30]. Zhang, J., Yao, C., & Sun, H. (2018). Learning context-aware convolutional neural networks for brain tumor segmentation. In 2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018) (pp. 172-175). IEEE.
[31]. Perez, L., & Wang, J. (2017). The effectiveness of data augmentation in image classification using deep learning. arXiv preprint arXiv:1712.04621.
[32]. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press. [33]. Nair, V., & Hinton, G. E. (2010). Rectified linear units improve restricted Boltzmann machines. In Proceedings of the 27th International Conference on Machine Learning (ICML-10) (pp. 807-814). [34]. Zeiler, M. D., & Fergus, R. (2014). Visualizing and understanding convolutional networks. In European Conference on Computer Vision (pp. 818-833). Springer, Cham.
[35]. Vincent, P., Larochelle, H., Lajoie, I., Bengio, Y., & Manzagol, P. A. (2010). Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion. Journal of Machine Learning Research, 11(12).
[36]. Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. Advances in Neural Information Processing Systems, 25. [37]. Dosovitskiy, A., Springenberg, J. T., & Brox, T. (2015). Learning to generate chairs, tables and cars with convolutional networks. IEEE Transactions on Pattern Analysis and Machine Intelligence, 39(4), 692-705.
[38]. Simard, P. Y., Steinkraus, D., & Platt, J. C. (2003). Best practices for convolutional

[39]. Aggarwal, M., Tiwari, A. K., Sarathi, M. P., & Bijalwan, A. (2023). An early detection and segmentation of Brain Tumor using Deep Neural Network. *BMC Medical Informatics and Decision Making*, *23*(1), 78.

[49]. Mostafa, A. M., Zakariah, M., & Aldakheel, E. A. (2023). Brain tumor segmentation using deep learning on MRI images. *Diagnostics*, *13*(9), 1562.

[41]. Zheng, P., Zhu, X., & Guo, W. (2022). Brain tumour segmentation based on an improved U-Net. *BMC Medical Imaging*, *22*(1), 199.

[42]. Saluja, S., Trivedi, M. C., & Dubey, A. K. (2023, April). U-Net Variants for Brain Tumor Segmentation: Performance and Limitations. In *2023 International Conference on Computational Intelligence, Communication Technology and Networking (CICTN)* (pp. 612-616). IEEE.

[43]. Das, S. (2020). Brain tumor segmentation from MRI images using deep learning framework. In *Progress in Computing, Analytics and Networking: Proceedings of ICCAN 2019* (pp. 105-114). Springer Singapore.
[44]. Liu, Z., Tong, L., Chen, L., Jiang, Z., Zhou, F., Zhang, Q., ... & Zhou, H. (2023). Deep learning based brain tumor segmentation: a survey. *Complex & intelligent systems*, *9*(1), 1001-1026.

Bibliography

[45]. Jyothi, P., & Singh, A. R. (2023). Deep learning models and traditional automated techniques for brain tumor segmentation in MRI: a review. Artificial intelligence review, 56(4), 2923-2969.

[46]. Brahim, I., Fourer, D., Vigneron, V., & Maaref, H. (2019, November). Deep learning methods for MRI brain tumor segmentation: a comparative study. In 2019 Ninth International Conference on Image Processing Theory, Tools and Applications (IPTA) (pp. 1-6). IEEE.
[47]. Hao, J., Li, X., & Hou, Y. (2020). Magnetic resonance image segmentation based on multi-scale convolutional neural network. IEEE Access, 8, 65758-65768.
[48]. Zahoor, M. M., Qureshi, S. A., Bibi, S., Khan, S. H., Khan, A., Ghafoor, U., & Bhutta, M. R. (2022). A new deep hybrid boosted and ensemble learning-based brain tumor analysis using MRI. Sensors, 22(7), 2726.

[49]. Google Colaboratory - https://research.google.com/colaboratory/faq.html [50]. TensorFlow - M. Abadi et al., "TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems," 2015. [Online]. Available: https://www.tensorflow.org/. [Accessed: 02-Jan-2022]. [51]. .Keras - F. Chollet et al., "Keras," GitHub, 2015. [Online]. Available: https://github.com/keras-team/keras. [Accessed: 02-Jan-2022].

[52]. NumPy - S. Van Der Walt, S. C. Colbert, and G. Varoquaux, "The NumPy Array: A Structure for Efficient Numerical Computation," Computing in Science & Engineering, vol. 13, no. 2, pp. 22–30, Mar. 2011.

[53]. Pandas - W. McKinney, "Data Structures for Statistical Computing in Python," Proceedings of the 9th Python in Science Conference, vol. 445, pp. 56–61, 2010.

[54]. OpenCV - G. Bradski, "The OpenCV Library," Dr. Dobb's Journal of Software Tools, vol. 25, no. 11, pp. 120–126, Nov. 2000.

[55]. Scikit-image - S. van der Walt, J. L. Schönberger, J. Nunez-Iglesias, F. Boulogne, J. D. Warner, N. Yager, E. Gouillart, T. Yu, and the scikit-image contributors, "scikit-image: Image processing in Python," PeerJ, vol. 2, p. e453, Jun. 2014.

[56]. Matplotlib - J. D. Hunter, "Matplotlib: A 2D Graphics Environment," Computing in Science & Engineering, vol. 9, no. 3, pp. 90–95, May 2007.

[57]. Seaborn - M. Waskom et al., "mwaskom/seaborn: v0.11.2 (January 2021)," Zenodo, Jan. 2021, doi: 10.5281/zenodo.4479278.

[58] .BraTS Dataset - B. H. Menze et al., "The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)," IEEE Transactions on Medical Imaging, vol. 34, no. 10, pp. 1993–2024, Oct. 2015.

[59]. VGG19 - K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," 2014. [Online]. Available: https://arxiv.org/abs/1409.1556. [Accessed: 02-Jan-2022].

[60]. ResNet50 - K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," 2016. [Online]. Available: https://arxiv.org/abs/1512.03385. [Accessed: 02-Jan-2022].

[61]. U-Net - O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," 2015. [Online]. Available: https://arxiv.org/abs/1505.04597. [Accessed: 02-Jan-2022].