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Brain Tumor Classification and Segmentation Using Deep Convolutional Neural Networks

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Introduction

Introduction

Brain Tumor is a condition that occurs due to the growth of abnormal tissue or neuronal cells in an area of the brain that can spread and modify brain structure.

Brain Tumors are one of the deadliest diseases ever identified. These abnormal cells grow unnaturally and uncontrollably. **Glioma**, **Meningioma**, and **Pituitary** tumors are the three most frequently diagnosed types of brain tumors.

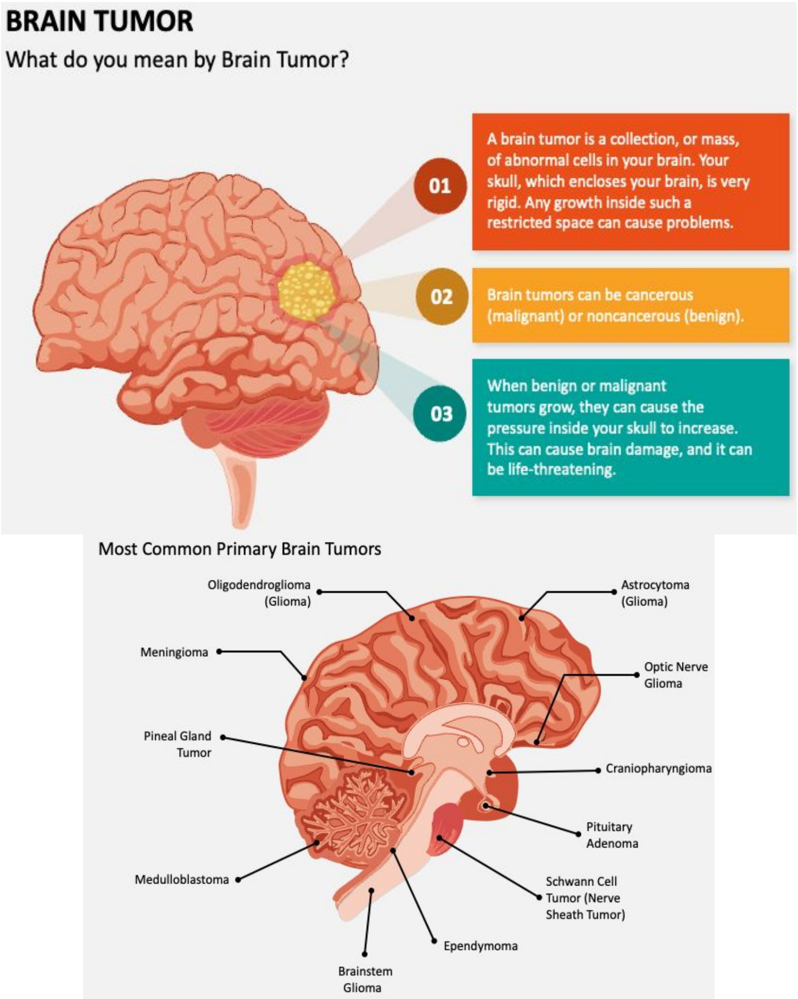

Figure 1. Brain Tumor Overview

Introduction

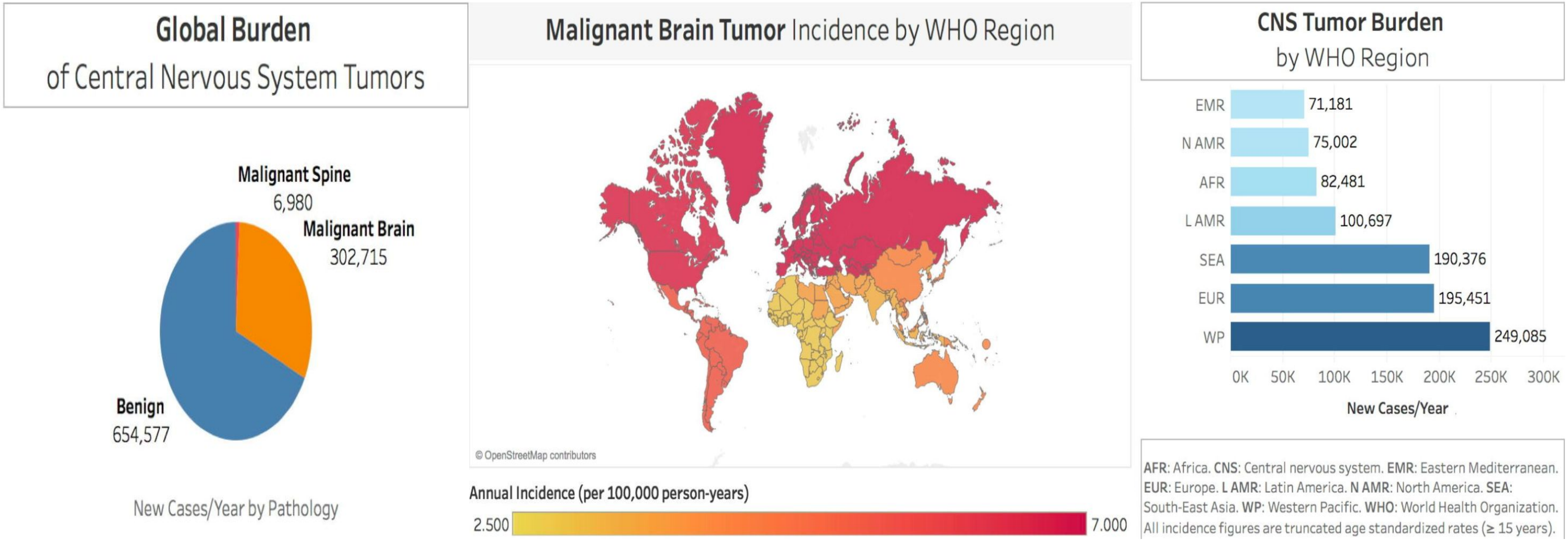

Figure 2. Global Incidence of Malignant and Benign Brain Tumors Dashboard

Problem Statement

Problem Statement

- Early brain tumor detection is critical due to subjective diagnostic limitations and the complexity of asymptomatic cases.
- Automated segmentation and classification of medical images are essential for efficient diagnostics and treatment planning. Manual procedures are time-intensive, emphasizing the need for automated detection.
- Deep learning plays a crucial role in streamlining brain tumor analysis, reducing time and effort in diagnostics.

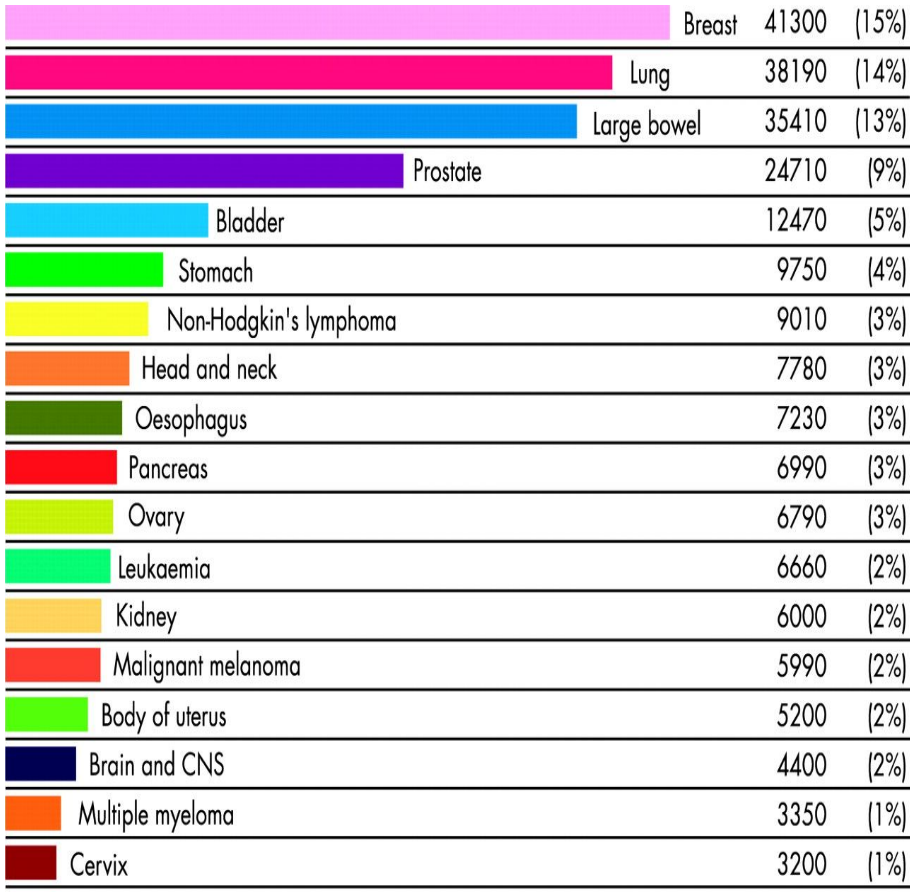

Figure 3. Overall Tumor Incidence % Worldwide

Literature Review

Literature Review

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Table 1. Literature Review of Classification Task

No	Topic	Dataset	Pre-Processing Method	Methods	Results
1	Brain Tumor Classification Using Dense Efficient-Net	Figshare	Gaussan and Laplacian Filter Fuzzy Membership Function Data Augmentation	Dense EfficientNet	• Accuracy = 98.78% • F-Score = 0.9875 • Precision = 0.9875
2	Brain tumor segmentation using deep learning on MRI images	BraTS 2020	-	Fuzzy C-Means VGG-16	• Accuracy = 96.70% • F-Score = 0.9705 • Precision = 0.9705 • Sensitivity = 0.9705 • Specificity = 0.9625
3	Brain Tumor Classification Using Convolutional Neural Network	Figshare	Image Resizing Gaussian Filter Histogram Equalization	Proposed CNN	• Accuracy = 94.39% • F-Score = 0.9333 • Precision = 0.9333 • Recall = 0.9300

Literature Review

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Table 2. Literature Review of Segmentation Task

No	Topic	Dataset	Pre-Processing Method	Methods	Results
4	Deep Convolutional Neural Networks Using U-Net for Automatic Brain Tumor Segmentation in Multimodal MRI Volumes	BraTS 2018	Normalization Data Augmentation	U-Net	• Dice Coefficient = 0.8187
5	Automatic Brain Tumor Detection and Segmentation Using U-Net Based Fully Convolutional Networks	BraTS 2015	Normalization	U-Net	• Dice Coefficient = 0.8567

Methodology

Methodology

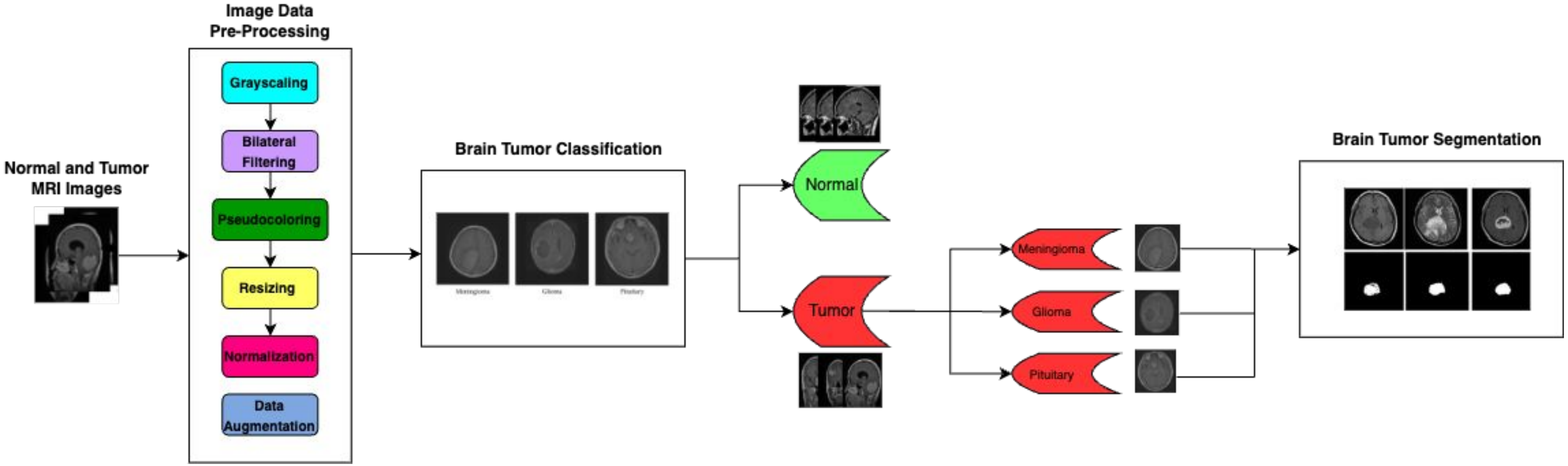

Figure 4. Methodology Flowchart Diagram

Data Acquisition & Image Pre-Processing

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Classification Data Acquisition

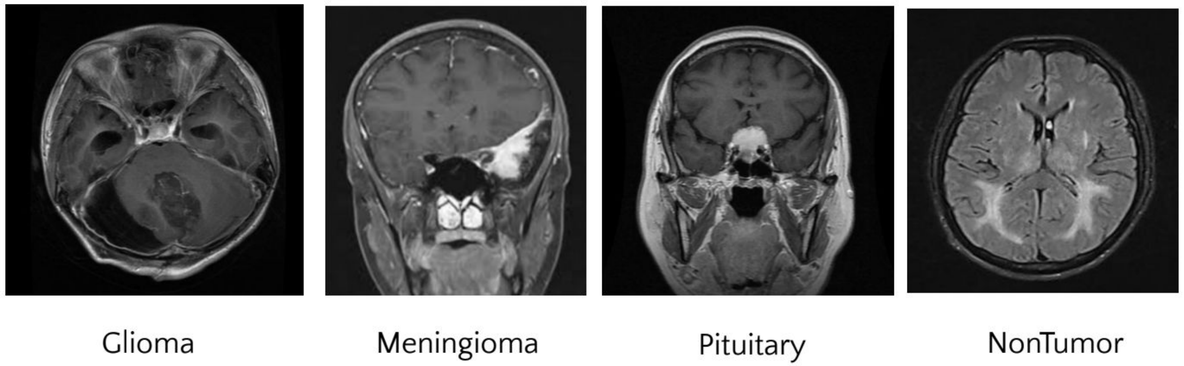

Figure 5. Classification Dataset Samples

Data of normal and tumor MRI Images from Masoud Nickparvar's Brain Tumor MRI **Kaggle** Dataset.

The dataset contains **7023 human brain MRI images** divided into **4** classes:

- **Glioma**
- **Meningioma**
- **Pituitary**
- **NonTumor**

Segmentation Data Acquisition

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Segmented MRI Images from Nikhil Tomar’s Brain Tumor Segmentation **Kaggle** Dataset.

The dataset contain **3064** human **brain MRI images** divided into **3** classes with Masks of the Tumor Region:

- **Glioma**
- **Meningioma**
- **Pituitary**

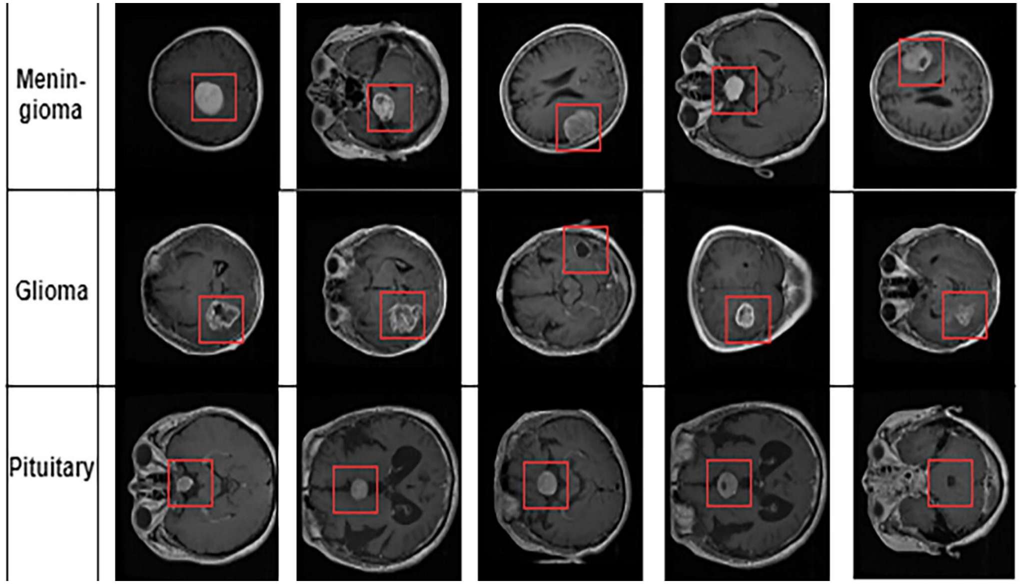

Figure 6. Segmentation Dataset Samples

Image Data Pre-Processing

Grayscaling:
Emphasizes intensity information in the images.

Bilateral Filtering
Preserves detailed structures while reducing noise in images.

Pseudocoloring
Enhances visualization of specific image characteristics.

Resize to 256x256
Standardizes image resolution for consistent analysis for the model.

Normalization
Scales pixel values to a common range. This helps our model learn faster and work well with different data variations.

Data Augmentation:
Makes our dataset more diverse by creating variations of existing images. This helps our model learn from different angles and positions, making it more versatile.

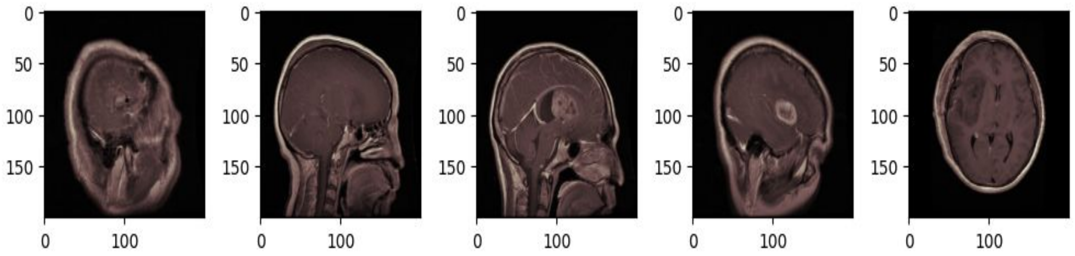

Figure 7. Pre-Processing Results

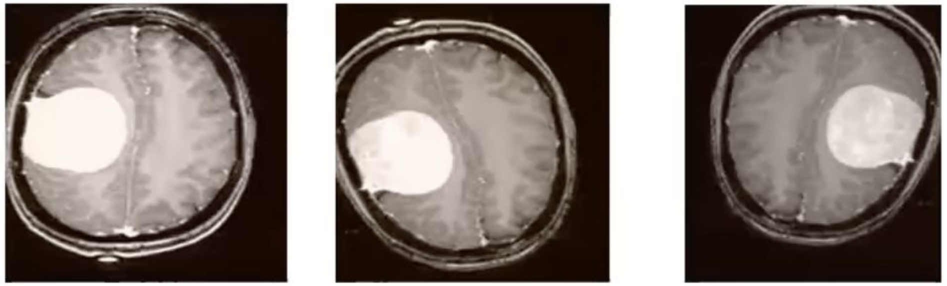

Figure 8. Data Augmentation Process

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Classification Modeling

Classification Modeling

Classification:

In our approach, we implement classification as a means to enhance the accuracy of the brain tumor segmentation. Performing classification will help to **differentiate different types of brain tumors** which in turn will provide assistance to the segmentation process. To develop the classification model, we will utilize the **EfficientNet** architecture. Specifically the **EfficientNetB0** and **EfficientNetB3** Variations.

The **smaller size and fewer parameters** of **EfficientNet** make it suitable for medical imaging tasks, especially when dealing with limited annotated datasets, as it can effectively complement the lack of annotated data affecting medical domains. Therefore, the efficiency, high accuracy, and resource optimization capabilities of **EfficientNet** make it a good choice for medical image classification tasks.

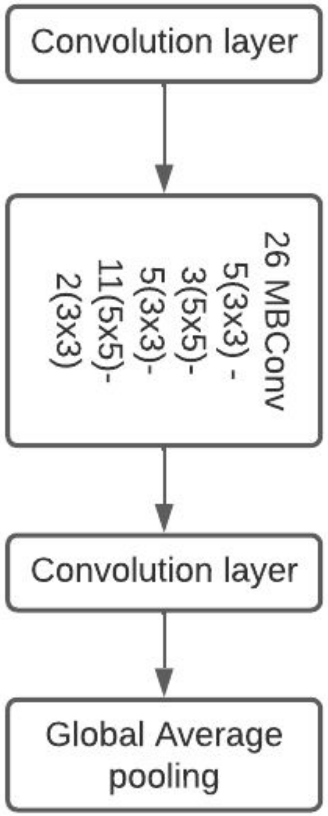

Figure 9. EfficientNet Base Model

Classification Modeling

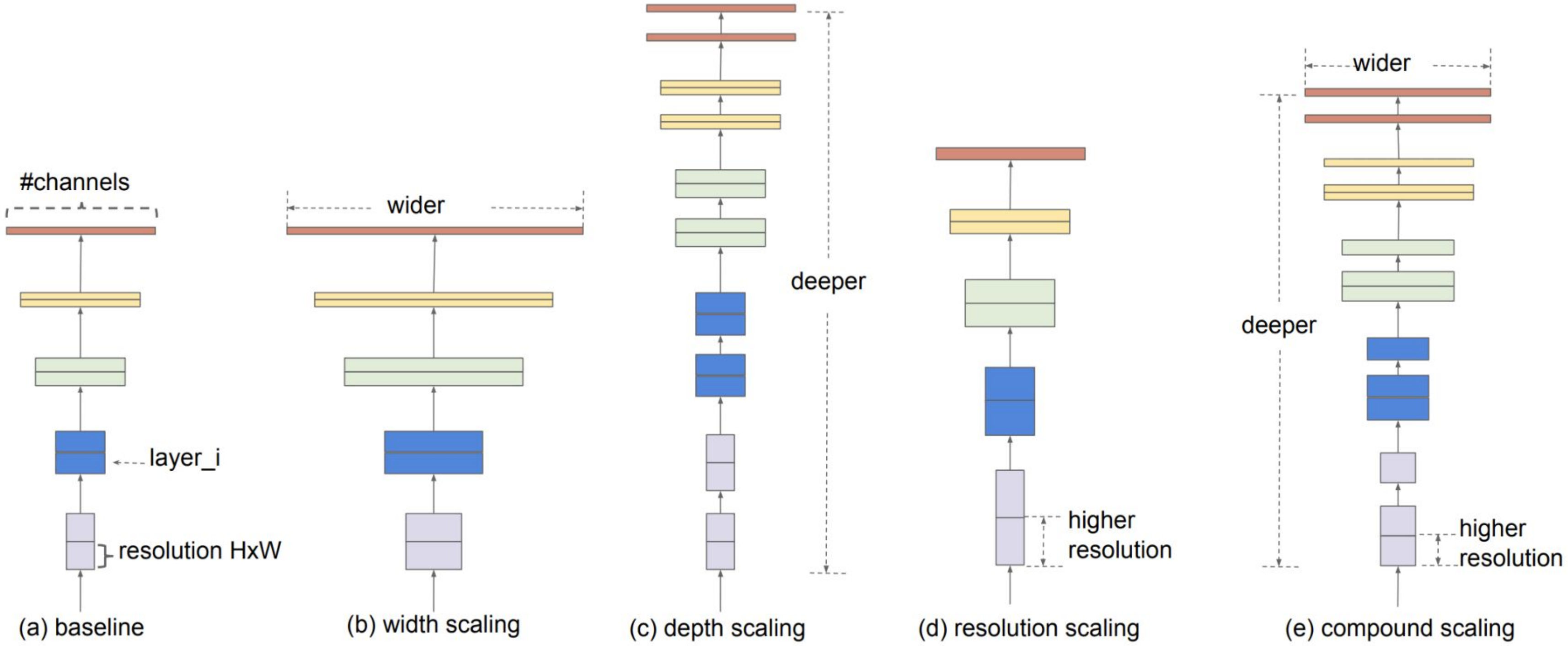

Figure 10. EfficientNet Compound Scaling

Classification Modeling

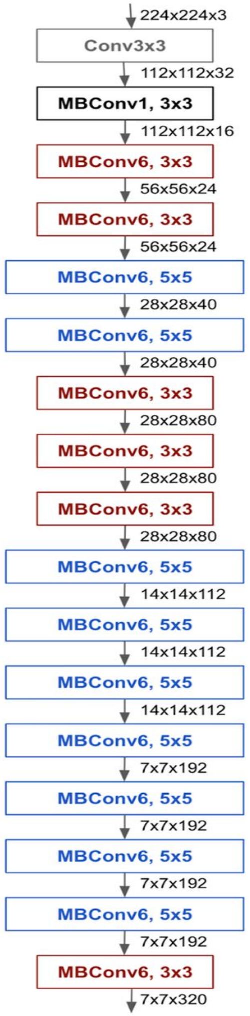

Figure 11. EfficientNetB0 Architecture

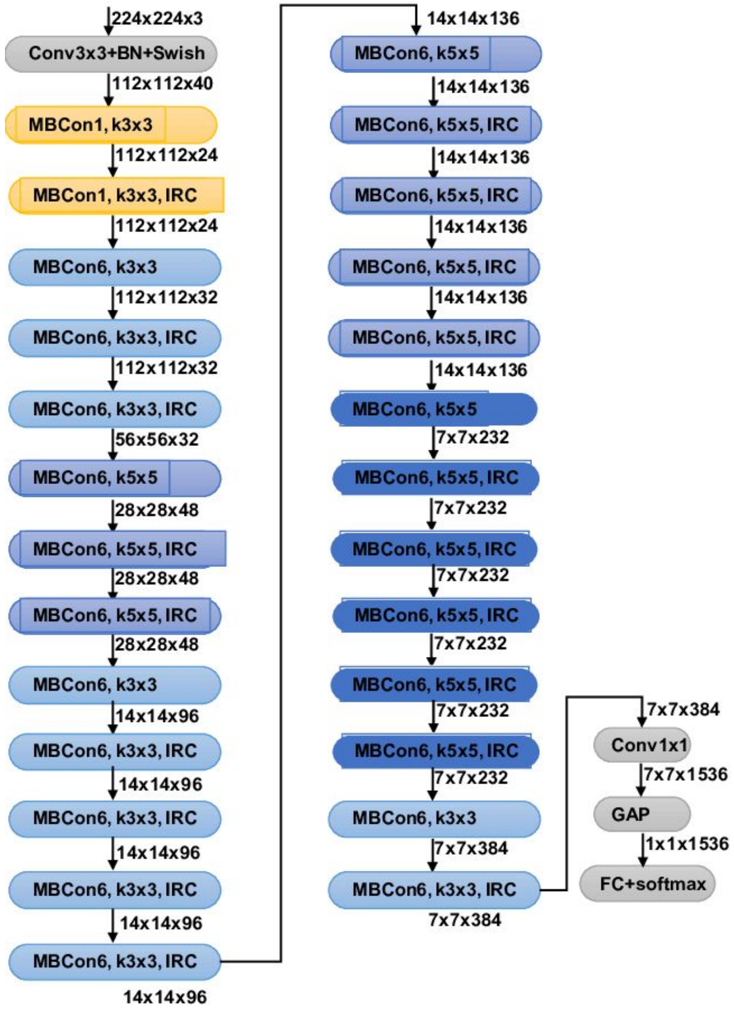

Figure 12. EfficientNetB3 Architecture

Segmentation Modeling

Segmentation Modelling

Segmentation:

To conduct segmentation, we employ the state-of-the-art **U-Net** Model, specifically designed for **biomedical image segmentation**.

This unique architecture allows the model to effectively segment tumor regions in medical images. The contracting path's convolutional operations enable the encoder to capture intricate features related to tumor characteristics, providing a high-level understanding of the input image.

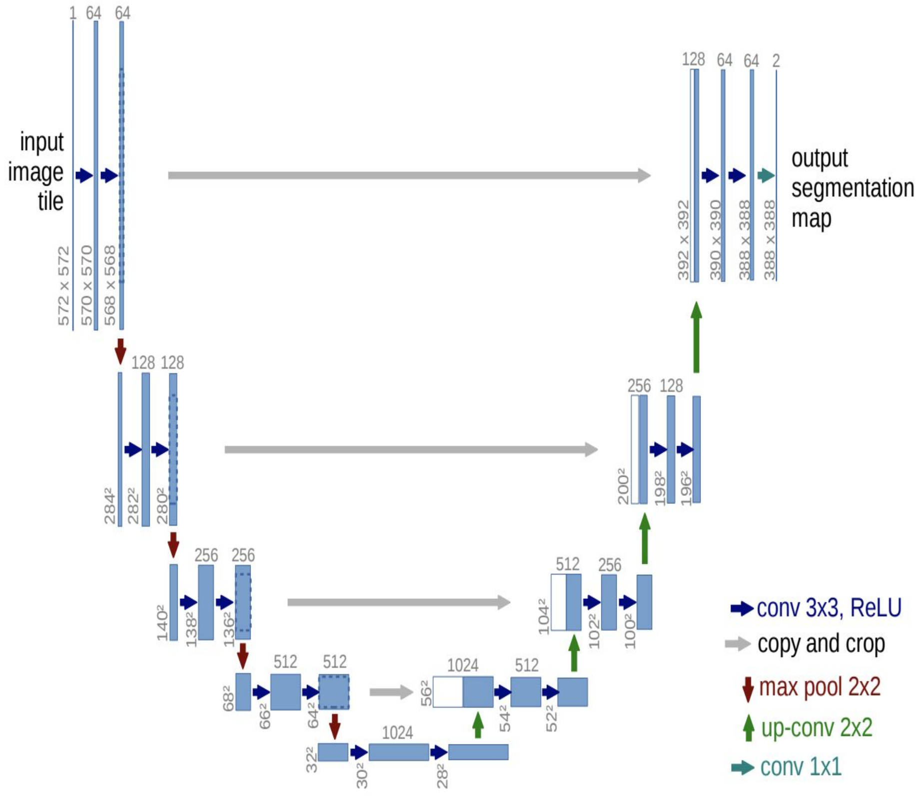

Figure 13. U-Net Architecture

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Results

Classification Results

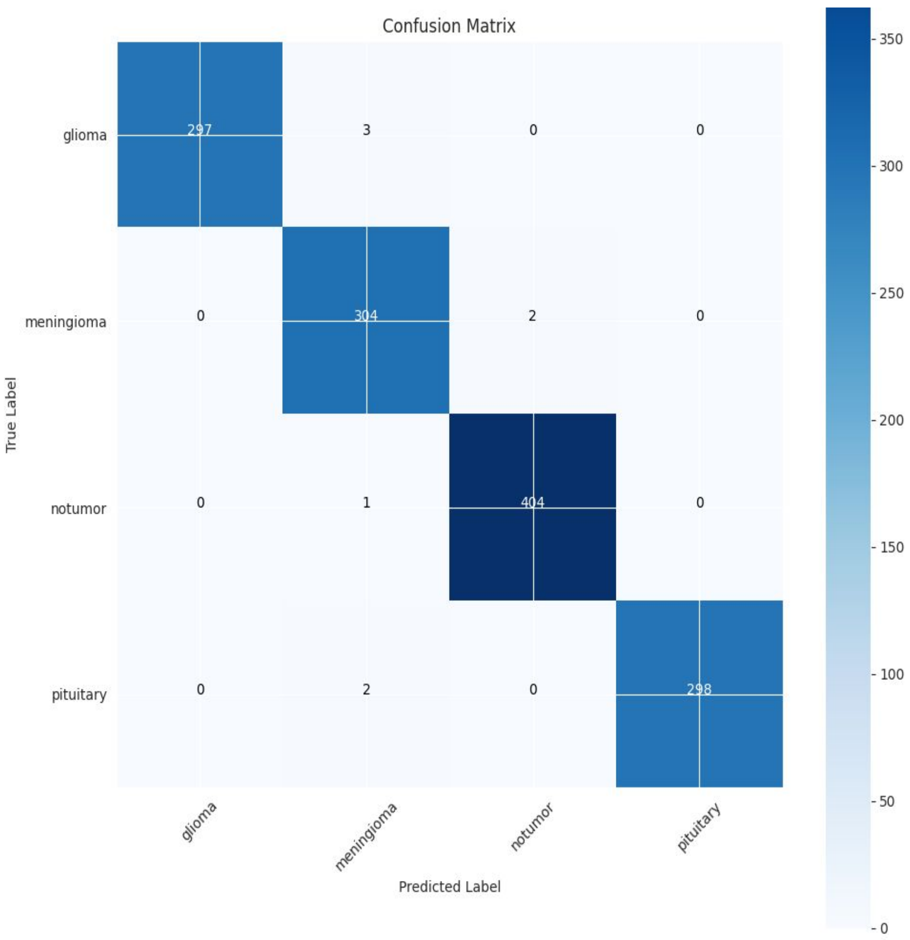

Figure 14. EfficientNetB0 Confusion Matrix

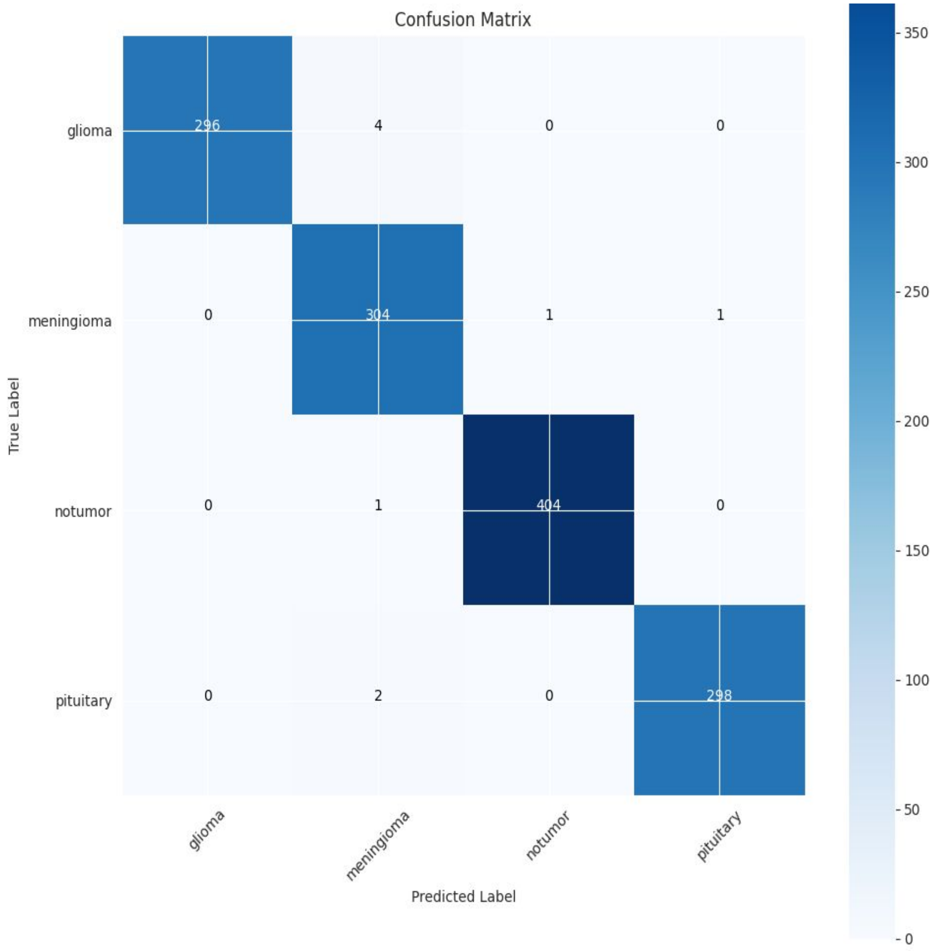

Figure 15. EfficientNetB3 Confusion Matrix

Segmentation Results

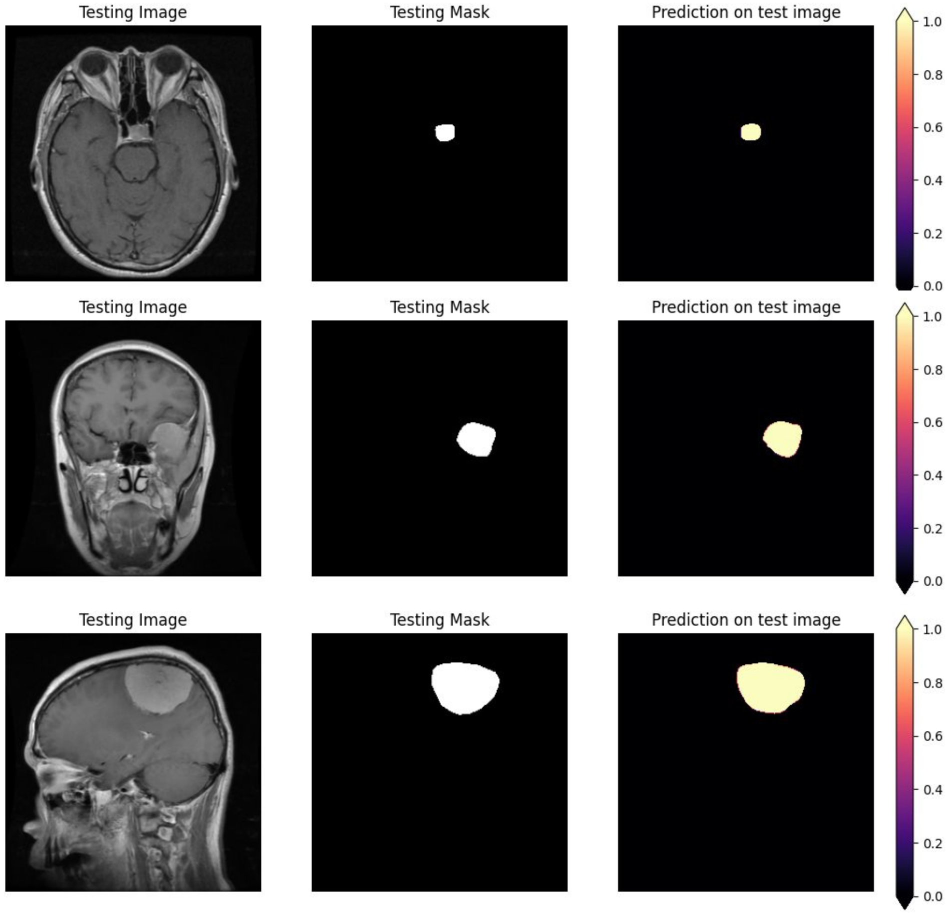

Figure 16. Segmentation Results

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Performance Evaluation

Performance Evaluation

Table 3. Classification Report

Model	*Accuracy*	*Recall*	*Precision*	*F1-Score*
EfficientNetB0	99.39%	0.99	0.99	0.99
EfficientNetB3	99.31%	0.99	0.99	0.99

Table 4. Segmentation Report

Model	*Accuracy*	*IoU*	*Dice Coefficient*
U-Net	99.97%	0.890	0.905

Classification Learning Curves

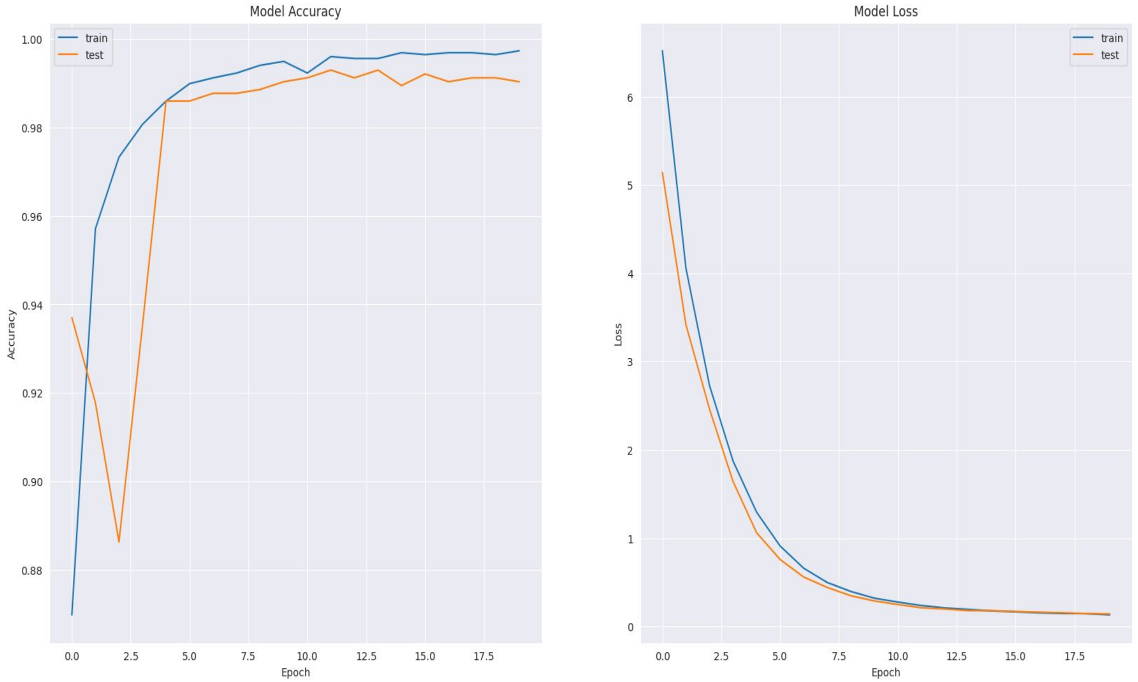

Figure 17. EfficientNetB0 Learning Curves

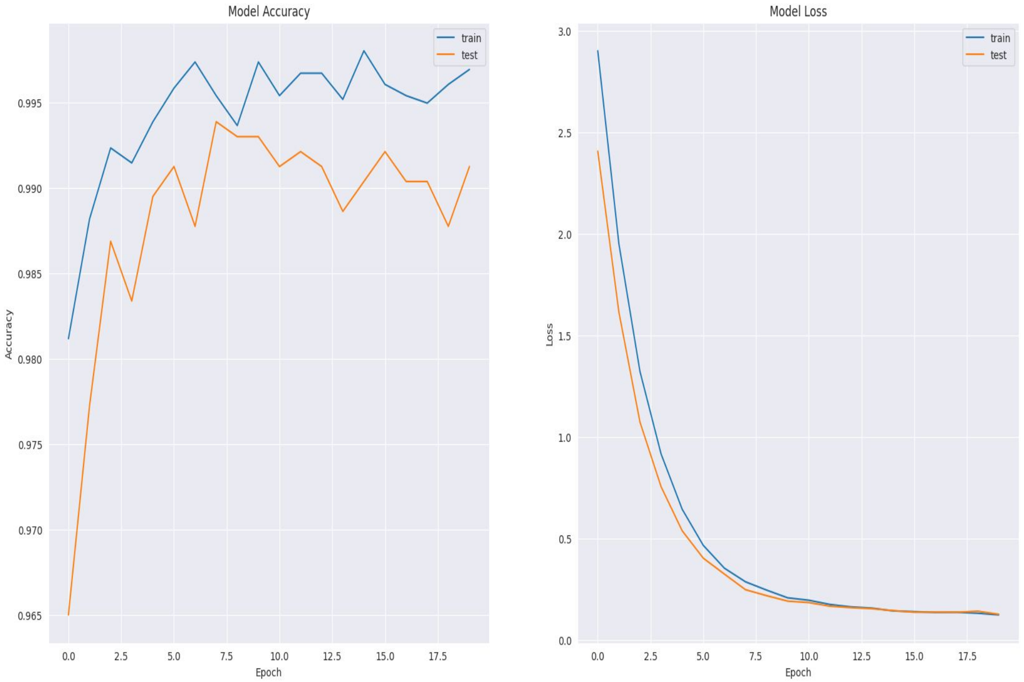

Figure 17. EfficientNetB3 Learning Curves

Segmentation Learning Curves

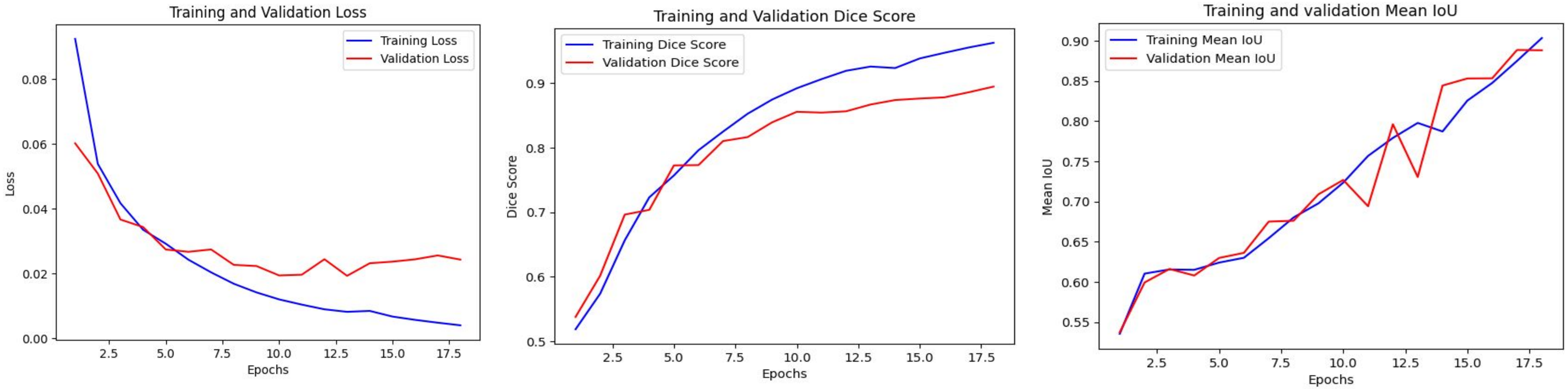

Figure 18. Learning Curves of U-Net

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Conclusion

Conclusion

EfficientNet and **U-Net** models showcase exceptional accuracy, surpassing **99%**, and achieve an IoU score of **89%**, highlighting their proficiency in brain tumor classification and segmentation.

The models demonstrate resilience in handling challenging scenarios, such as varying perspectives in MRI images, while maintaining heightened accuracy, underscoring the robust nature of deep learning in addressing complexities of brain tumor detection.

The successful implementation of these advanced models not only refines segmentation quality and accuracy but also holds promising implications for automating detection systems through advanced image analysis and deep learning, shaping the future of medical imaging.

Future improvements could explore the integration of other deep learning methods, such as **VGG-16** and **ResNet50**, or consider a **Hybrid Ensemble Learning** approach to further enhance the capabilities of brain tumor detection systems through advanced image analysis.

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Thank You!

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