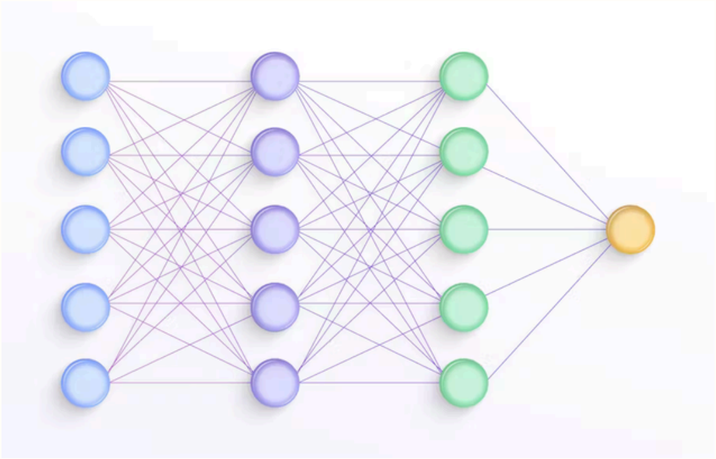
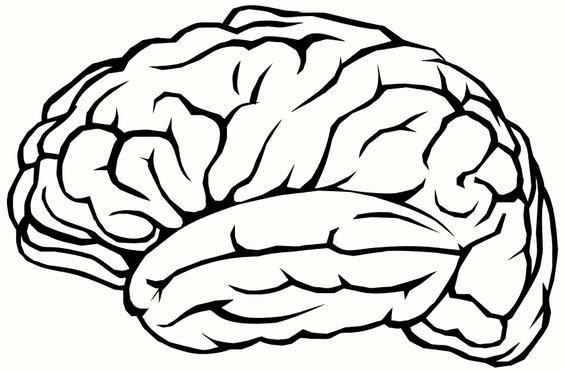
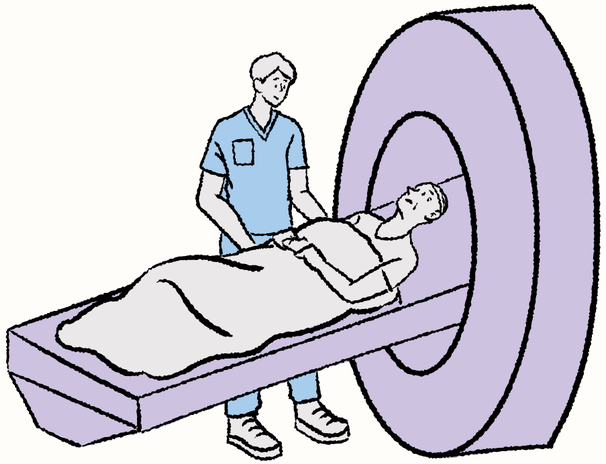




AUTOMATED CLASSIFICATION AND SEGMENTATION OF BRAIN TUMORS IN MRI SCANS



Presented by
Juin Tan (20913887)

YOUTUBE LINK: HTTPS://YOUTU.BE/-U4V2TDUTQC

Table of Contents

01. Background Information

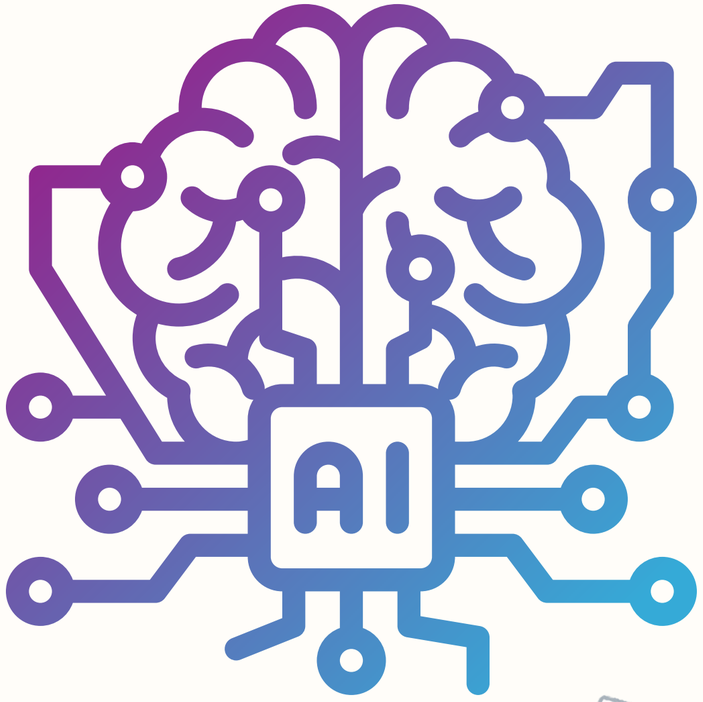
01. Background Information

- **Aggressive Cancer Type**
  - Critical impact on survival rates
- **Survival Statistics**
  - Nearly 70% of malignant cases are fatal (Roswell Park, 2022)
- **Role of MRI**
  - Detailed brain imaging for tumor visualization
- **Clinical Significance**
  - Essential for detection and management of tumors

01. Background Information

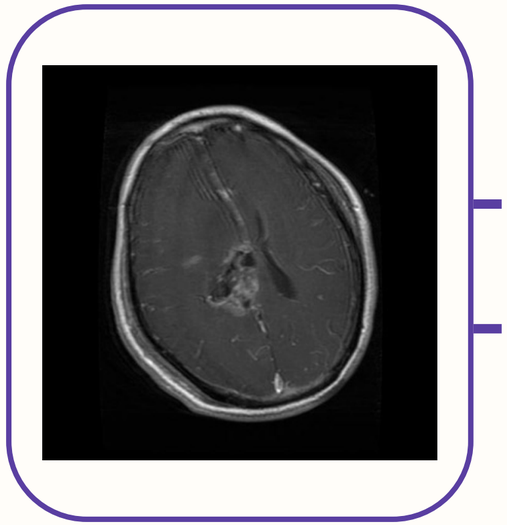
- **Labor-Intensive Process**
  - Time-consuming and prone to human error
- **Model Overview**
  - Streamlines MRI scan review
- **Benefits of Automation**
  - Saves time and reduces errors
  - Accelerates diagnostic processes

01. Background Information



- **Methodology**
  - Combines classification and instance segmentation
  - Both models trained on different datasets
    - Improved Accuracy in Predictions
    - Resilient for Clinical Applications
- **Detailed Reports Generated**
  - Actionable insights for healthcare providers
- **Potential for Earlier Interventions**
  - Faster diagnosis leads to timely treatments

Pipeline



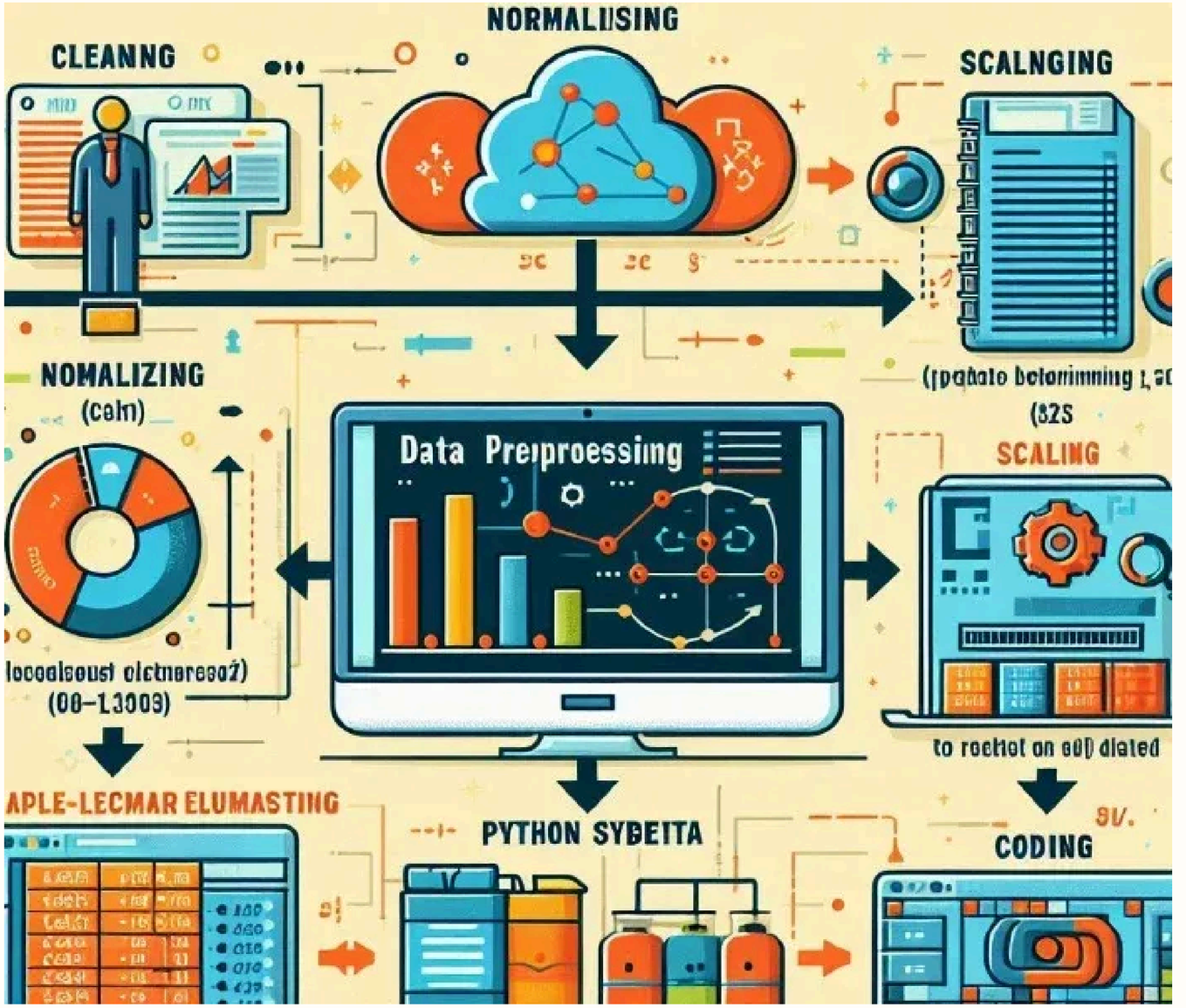
Patient MRI image

Classification Model

Segmentation Model

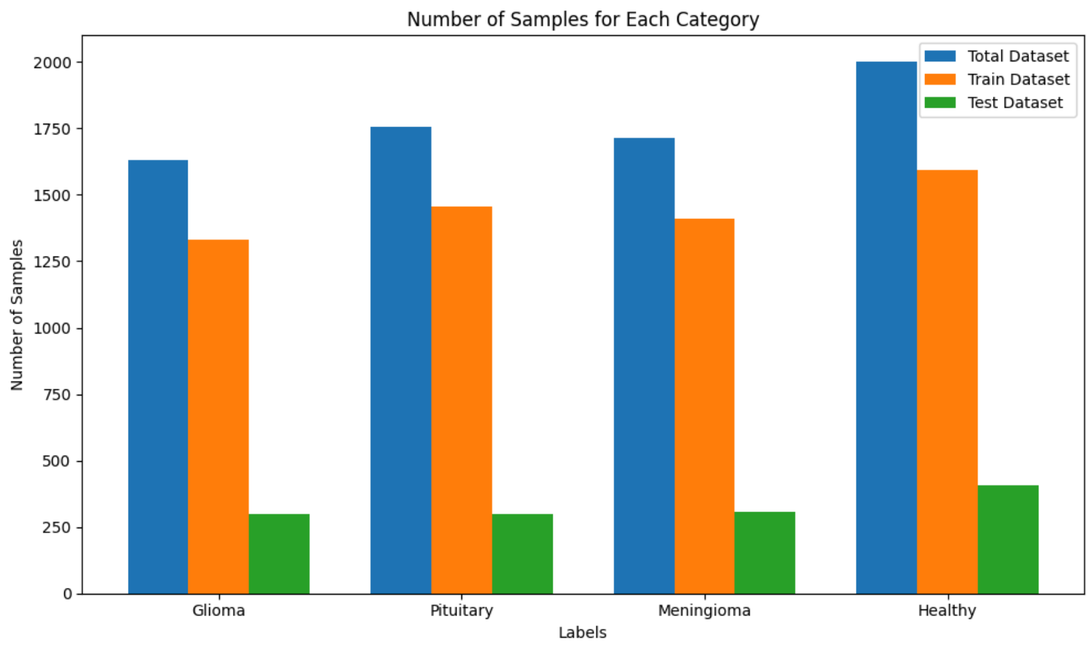
Generated Report

02. Dataset Description



02. Dataset Description

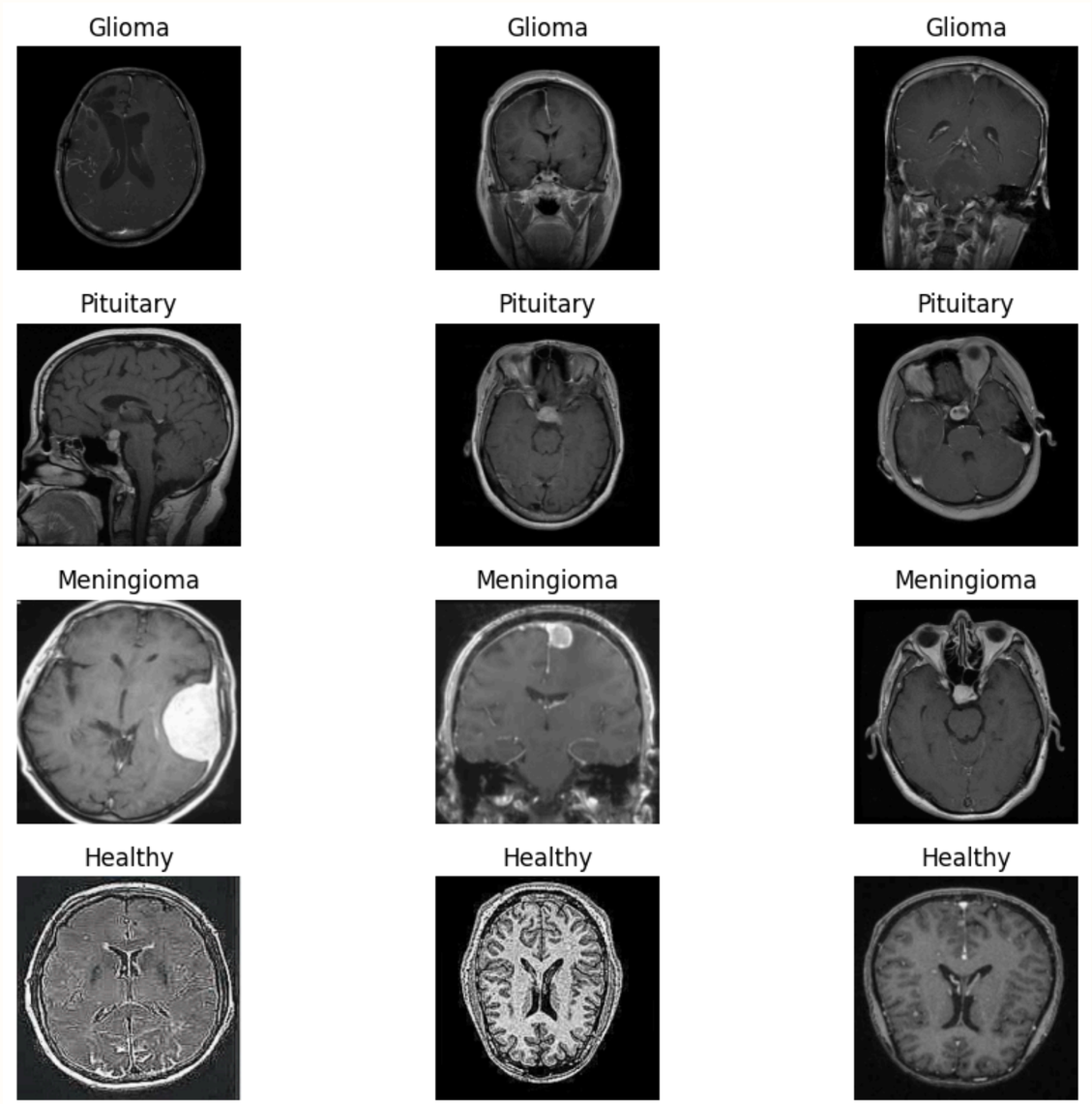
- **7,023 images categorized into four classes:**
  - Glioma Tumor
  - Meningioma Tumor
  - Pituitary Tumor
  - No Tumor



- **Structure**
  - Aggregation of three datasets: Figshare, SARTAJ, Br35H

- **Data Integrity**
  - Removed erroneous SARTAJ images; included accurate Figshare images

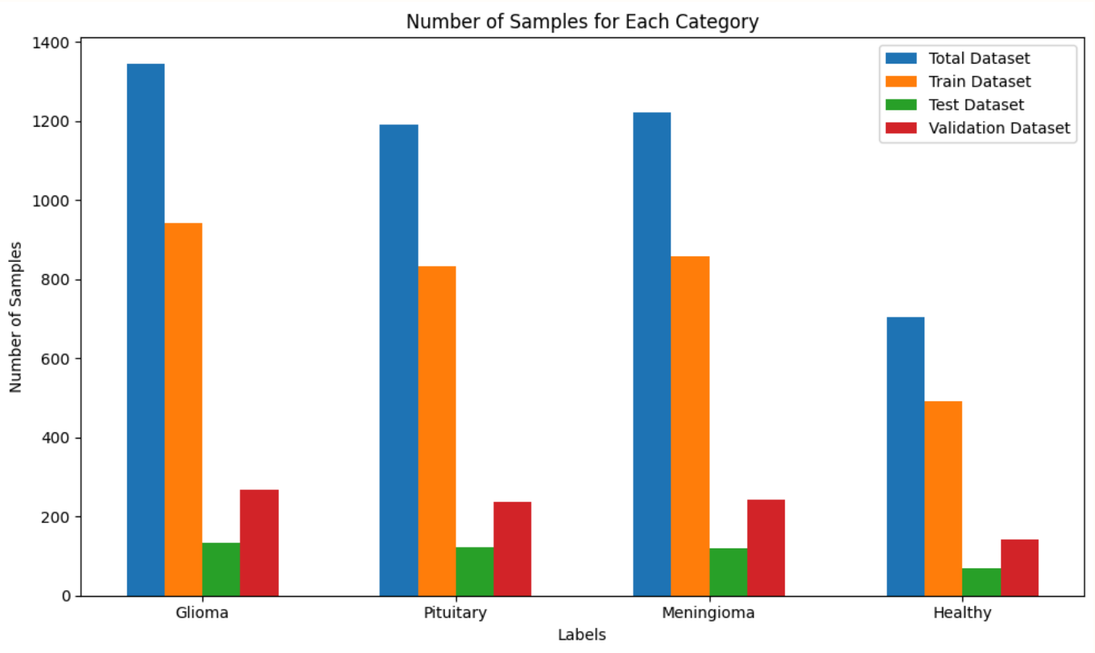
02. Dataset Description



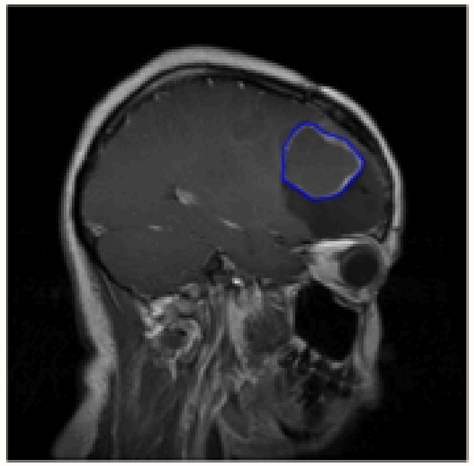
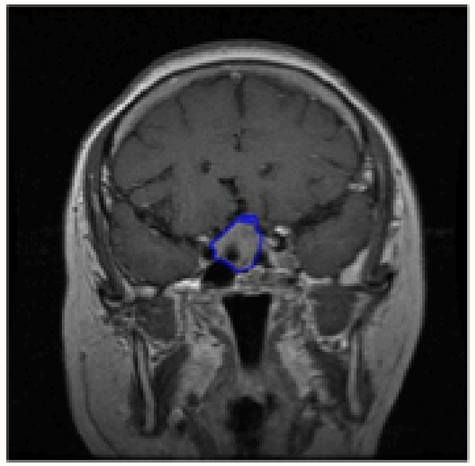
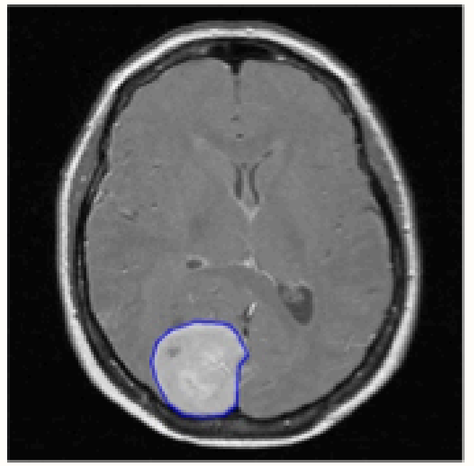
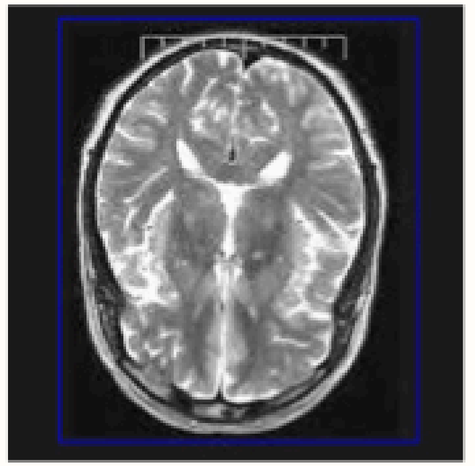
02. Dataset Description

- **4,462 images categorized into four classes:**
  - Glioma Tumor
  - Meningioma Tumor
  - Pituitary Tumor
  - No Tumor

- **Image Specifications**
  - All images resized to 640x640 pixles
  - Auto-orientation and EXIF stripping for consistency



02. Dataset Description

Glioma	Pituitary	Meningioma	Healthy
			

03. Machine Learning Task 1 (Classification Model)

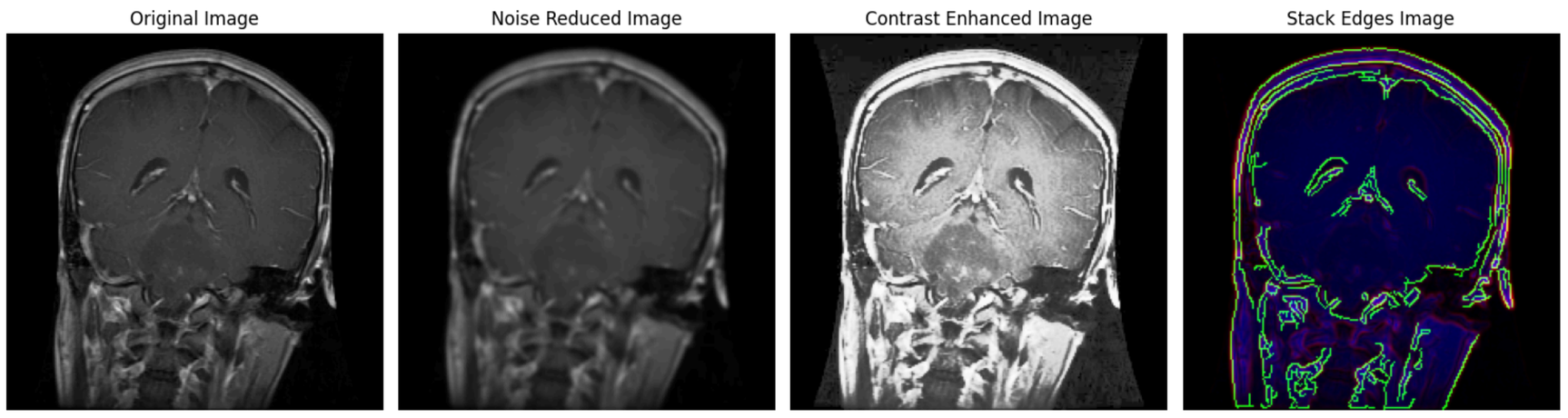
03. Preprocessing Techniques

- **Image Resizing**
  - All images resized to (224, 224)
- **Label Encoding**
  - One-hot encoding for the labels

03. Preprocessing Techniques

- **Image Resizing**
  - All images resized to (224, 224)
- **Label Encoding**
  - One-hot encoding for the labels

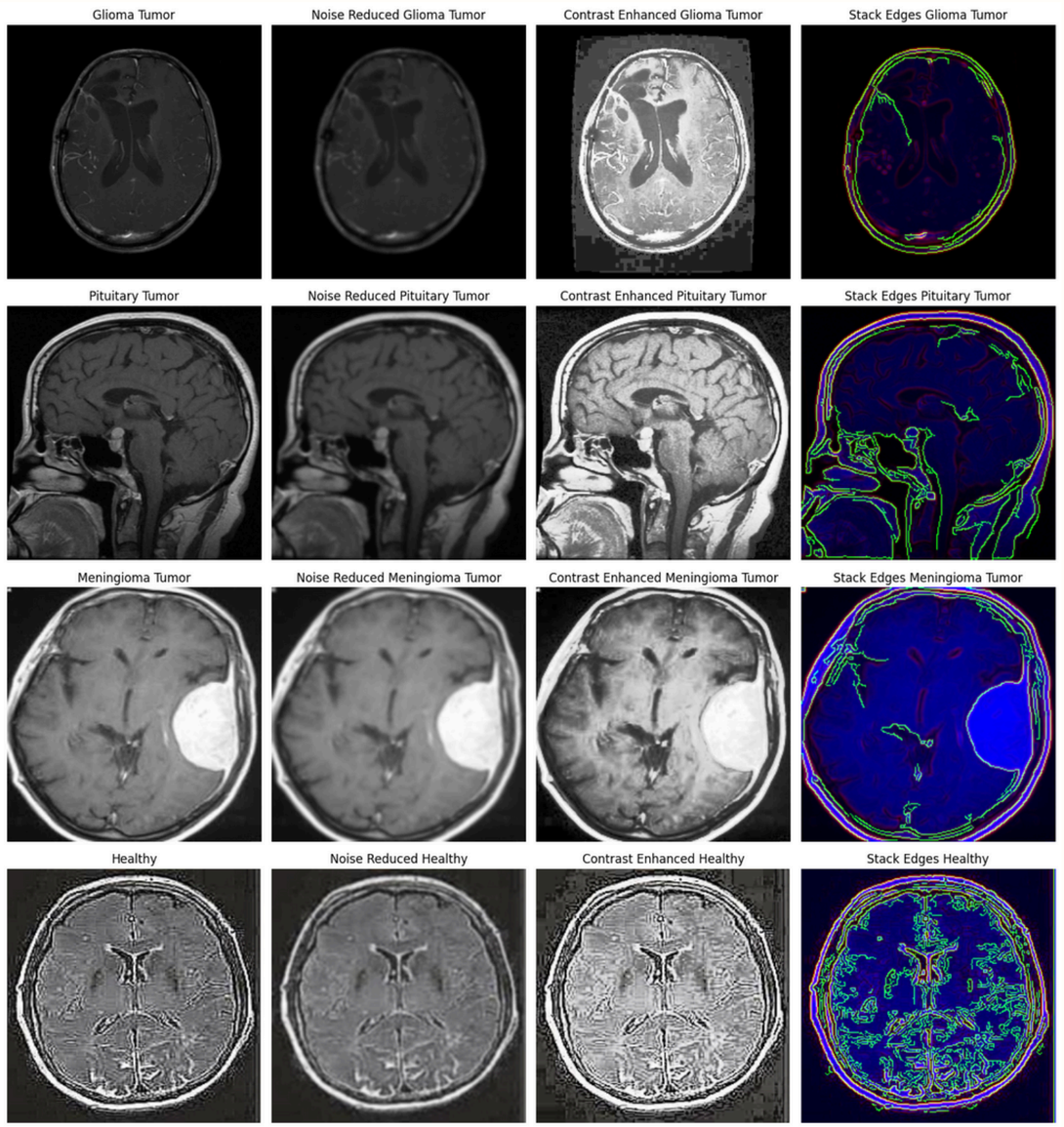
- **Preprocessing techniques**
  - Noise Reduction
  - Contrast Enhancement
  - Stacked Edges



03. Preprocessing Techniques

Preprocessing Techniques	Implementation	Advantages
Noise Reduction	Gaussian Blur Algorithm	Enhances signal-to-noise ratio
Constrast Enhancement	Contrast Limited Adaptive Histogram Equalization (CLAHE)	• Enhances local contrast • Prevents noise amplification
Stacked Edges	• Canny Edge Detection • Sobel Filter	• Emphasizes salient features • Enhances edge information for CNN learning

03. Preprocessing Techniques



03. Classification Model

Model	Preprocessing Technique Used
CNN Model	Resize images to (224, 224)
CNN Model	Resize images to (224, 224) + Noise Reduction
CNN Model	Resize images to (224, 224) + Constrast Enhancement
CNN Model	Resize images to (224, 224) + Stacked Edges
ResNet50 + CNN Model	Resize images to (224, 224)
ResNet50 + CNN Model	Resize images to (224, 224) + Stacked Edges
Vision Transformer (ViT) Model	Resize images to (224, 224)
Vision Transformer (ViT) Model	Resize images to (224, 224) + Stacked Edges

03. Classification Model

CNN Model

- **Input Layer:**
  - Accepts input images of shape (IMG_HEIGHT, IMG_WIDTH, 3) for RGB channels.

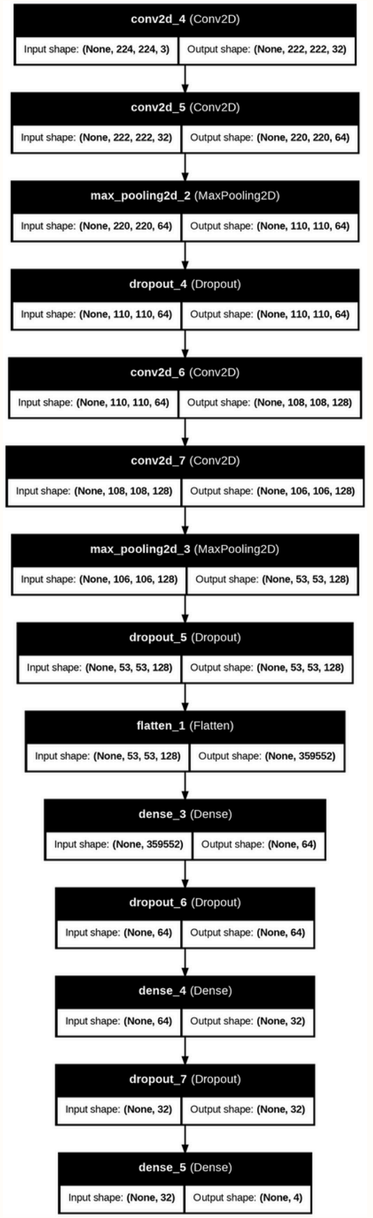
- **Convolutional Layers:** Multiple layers with increasing filters
  - **Conv Layer 1:** Extracts basic features from the input images.
  - **Conv Layer 2**: Captures more complex patterns.
  - **Conv Layer 3**: Further deepens the feature extraction.
  - **Conv Layer 4**: Enhance intricate feature learning.

- **Pooling Layers:**
  - Downsample the feature maps, reducing spatial dimensions while retaining essential features.

- **Dropout Layers:**
  - Applied after the pooling layers and dense layers to prevent overfitting.

- **Flatten Layer:**
  - Convert the 2D feature maps into a 1D feature vector, making it suitable for fully connected layers.

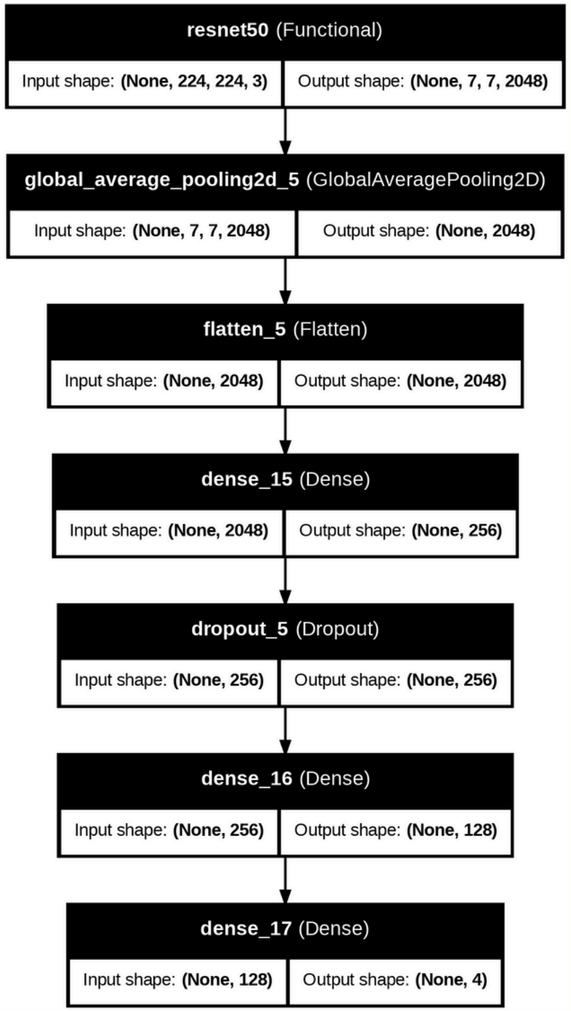
- **Fully Connected Layers:**
  - **First Dense Layer**: Contains L2 regularization to penalize large weights and promote model generalization.
  - **Second Dense Layer**: Contains L2 regularization and continue feature learning.
  - **Output Layer:** Output a probability distribution over the classes.



03. Classification Model

ResNet50 + CNN Model

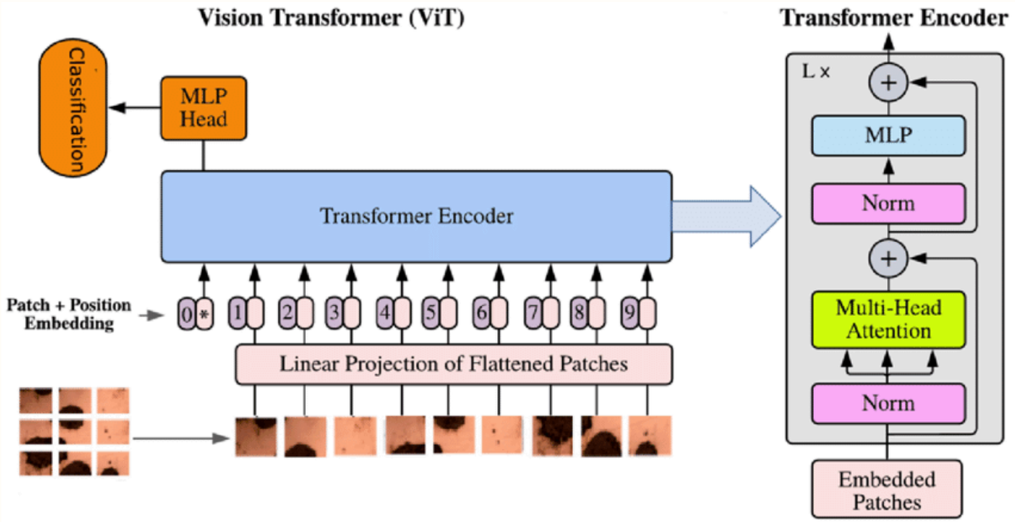
- **Input Layer:**
  - Accepts input images of shape (IMG_HEIGHT, IMG_WIDTH, 3) for RGB channels.
- **Base Model:**
  - Utilizes ResNet50 for feature extraction, excluding the top classification layers.
- **Pooling Layers:**
  - Downsample the feature maps, reducing spatial dimensions while retaining essential features.
- **Flatten Layer:**
  - Convert the 2D feature maps into a 1D feature vector, making it suitable for fully connected layers.
- **Dropout Layers:**
  - Applied after the dense layers to prevent overfitting.
- **Fully Connected Layers:**
  - **First Dense Layer**: Promotes non-linearity in feature representation.
  - **Second Dense Layer**: Refines the model's ability to learn complex patterns.
  - **Output Layer:** Output a probability distribution over the classes.



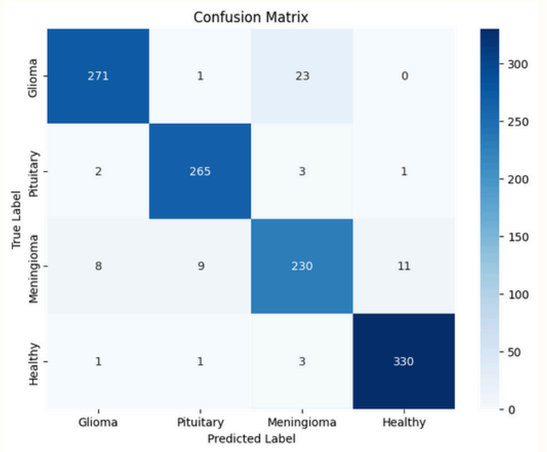
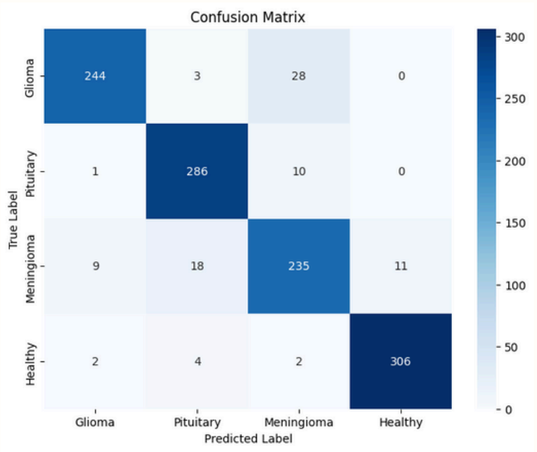
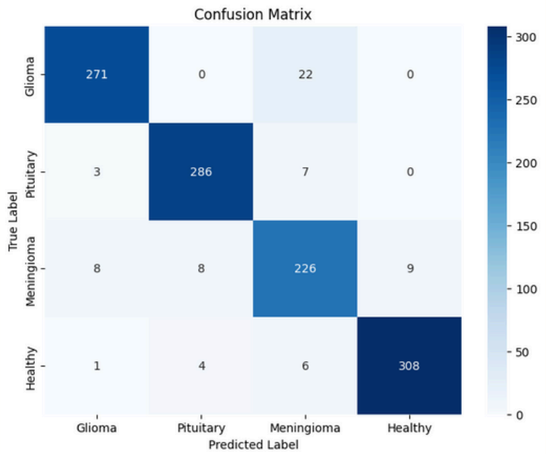
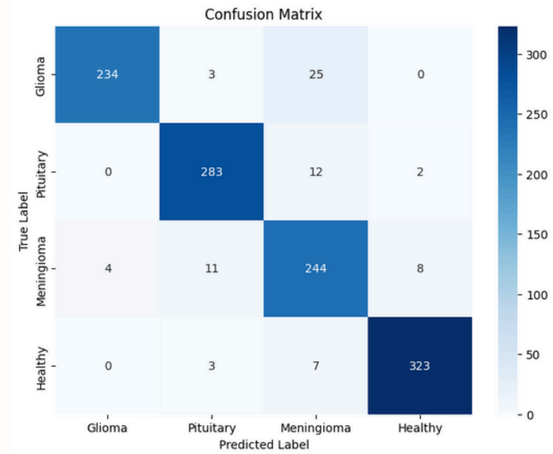
03. Classification Model

Vision Transformer (ViT) Model

- **Input Layer:**
  - Accepts input images of shape (IMG_HEIGHT, IMG_WIDTH, 3) for RGB channels.
- **Patch Extraction:**
  - Divides images into (16, 16) patches, reshaping input to (batch_size, num_patches, patch_size * patch_size * channels).
- **Dense Layer:**
  - Initial feature extraction from patches.
- **Multi-Head Attention Layers:**
  - Incorporates four attention layers with 8 heads each to capture complex dependencies among patches.
- **Global Average Pooling Layers:**
  - Recued output to a fixed-size representation, producing an output shape of (batch_size, d_model).
- **Output Layer:**
  - Output a probability distribution over the classes.



03. Results Obtained with Different Preprocessing Techniques

No Preprocessing	Noise Reduction	Contrast Enhancement	Stacked Edges
• Precision: 0.95 • Recall: 0.95 • F1-Score: 0.95 • Accuracy: 0.95	• Precision: 0.92 • Recall: 0.92 • F1-Score: 0.92 • Accuracy: 0.92	• Precision: 0.94 • Recall: 0.94 • F1-Score: 0.94 • Accuracy: 0.94	• Precision: 0.94 • Recall: 0.94 • F1-Score: 0.94 • Accuracy: 0.94
			

03. Analysis of the Results Obtained with Different Preprocessing Techniques

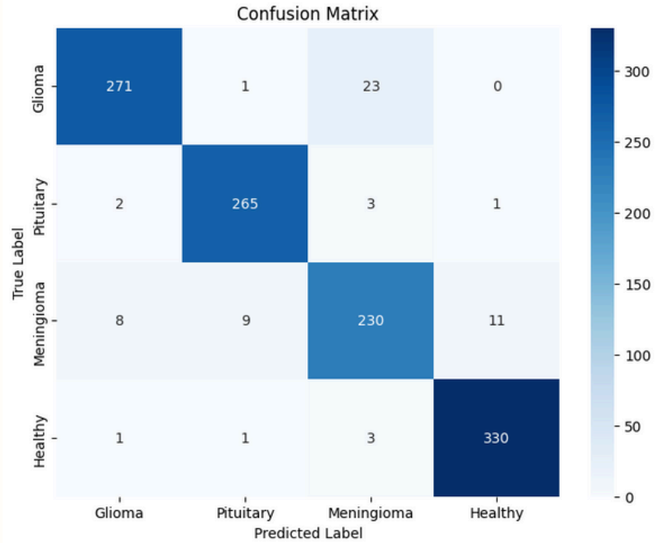
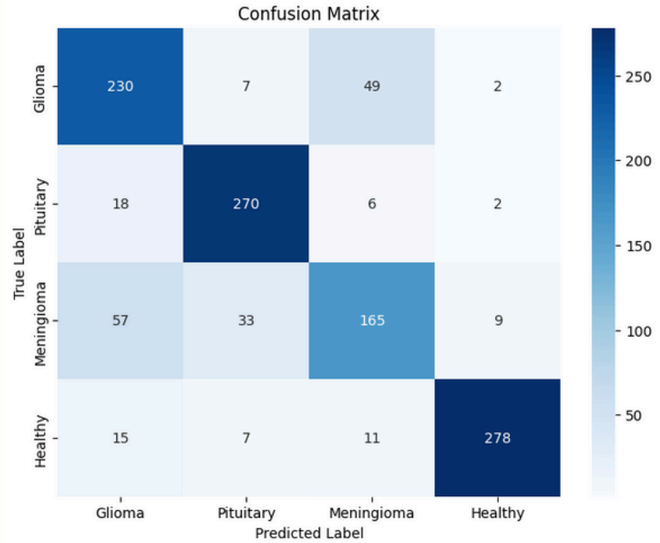
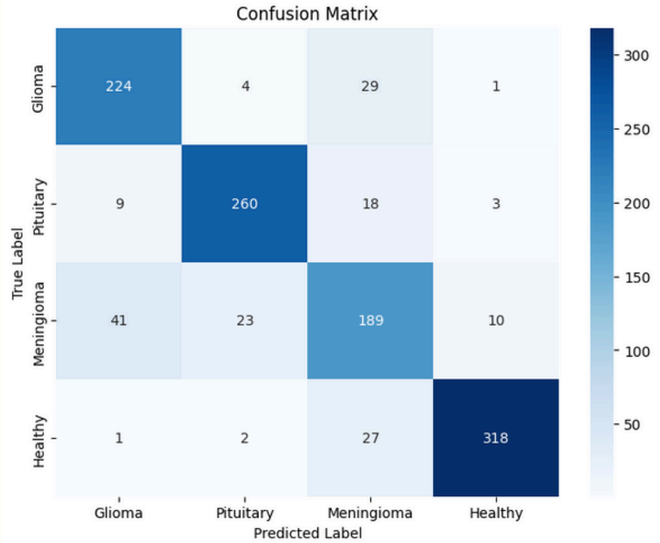
- **Performance**
  - **No Preprocessing:** Best performance
  - **Stacked Edges:** Moderate performance
  - **Contrast Enhancement:** Moderate performance
  - **Noise Reduction:** Worst performance

- **Why no preprocessing has the best performance?**
  - Dataset has a high quality
    - Careful assembly from **3** distinct datasets
    - Addressed class imbalance
    - Preprocessed to remove problematic samples

- **Technique Effectiveness**
  - Stacked Edges and Contrast Enhancement improved image quality but not accuracy
  - Noise Reduction may remove some crucial features

- **Notes**
  - Gliomas often misclassified as meningiomas
  - Similar features in MRI sequences complicate classification
  - Heterogeneity of gliomas adds complexity

03. Best Results Obtained on Different Models

CNN (No Preprocessing)	ResNet50 + CNN (Stacked Edges)	Vision Transformer (ViT) (Stacked Edges)
• Precision: 0.95 • Recall: 0.95 • F1-Score: 0.95 • Accuracy: 0.95	• Precision: 0.82 • Recall: 0.82 • F1-Score: 0.81 • Accuracy: 0.81	• Precision: 0.86 • Recall: 0.86 • F1-Score: 0.86 • Accuracy: 0.86
		

03. Analysis of the Best Results Obtained on Different Models

- **Performance**
  - **CNN:** Best performance without preprocessing
  - **ViT:** Improved performance with stacked edges technique
  - **ResNet50 + CNN:** Worst performance overall

- **Insights on Model Discrepancies**
  - **CNN:** Simpler architecture effective for powerful and robust dataset
  - **ResNet50 + CNN and ViT:** Struggled due to dataset mismatch and complexity

- **Limitations of Pre-trained Models**
  - **Feature Generalization:** Pre-trained models may not capture medical imaging nuances
  - **Data Size Requirement:** Complex architectures need larger datasets for optimal performance
  - **Training Epochs:** Complex architectures need more training epochs for optimal performance

- **Summary**
  - **CNN** performs well with the raw dataset we gathered
  - **ResNet50 + CNN** and **ViT** may need specialized preprocessing for MRI features

03. Machine Learning Task 2 (Segmentation Model)

04. Segmentation Model

U-Net Model

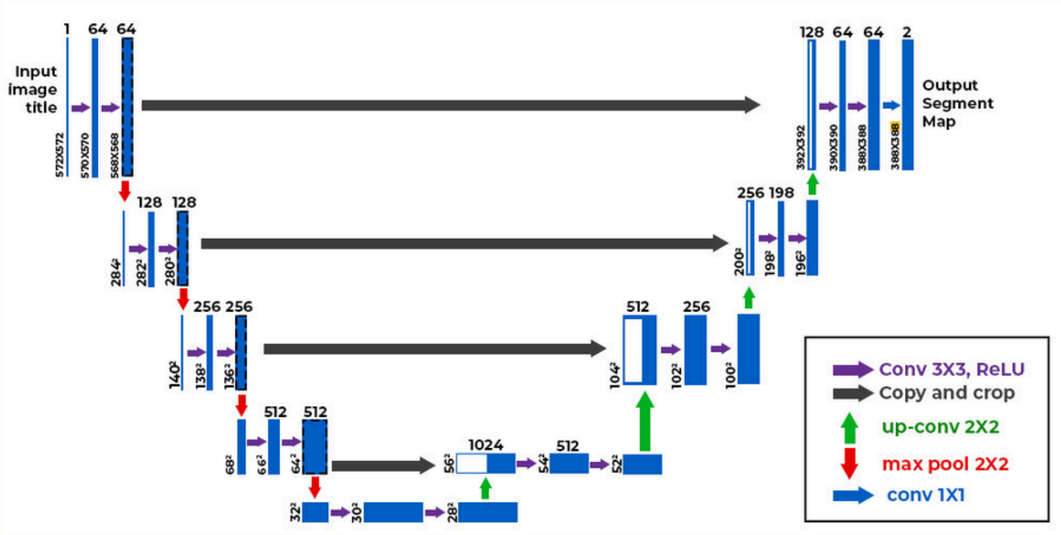
- **Input Layer:**
  - Accepts input images of shape (IMG_HEIGHT, IMG_WIDTH, 3) for RGB channels.

- **Contracting Path:**
  - **Convolutional Layers:** Extracts features at increasing levels of complexity.
  - **MaxPooling Layers:** Downsample feature maps, reducing spacial dimensions while retaining essential information.

- **Bottleneck Layer:**
  - Capture the most abstract features of the image.

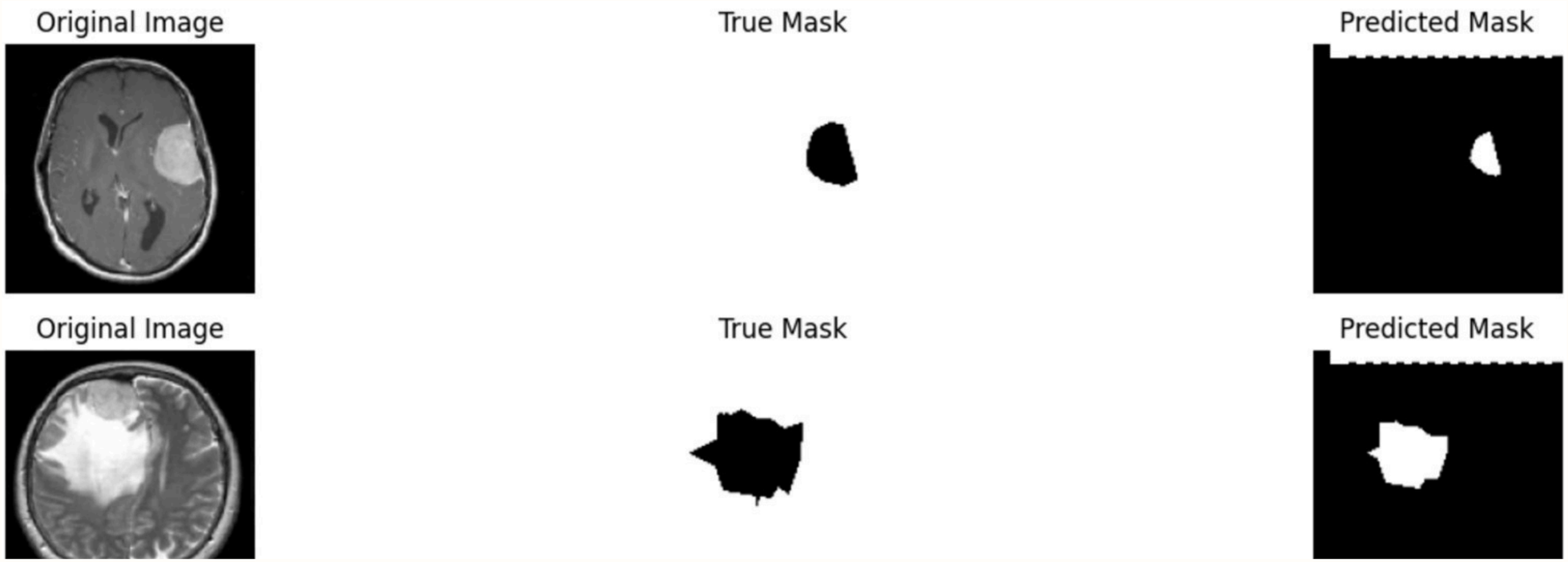
- **Expansive Path:**
  - **Transpose Convolutional Layers**: Upsample the feature maps to original image dimensions.
  - **Concatenation**: Combine features from the contracting path to retain spatial information.

- **Output Layer:**
  - Produces segmentation maps with the number of classes for each pixel.



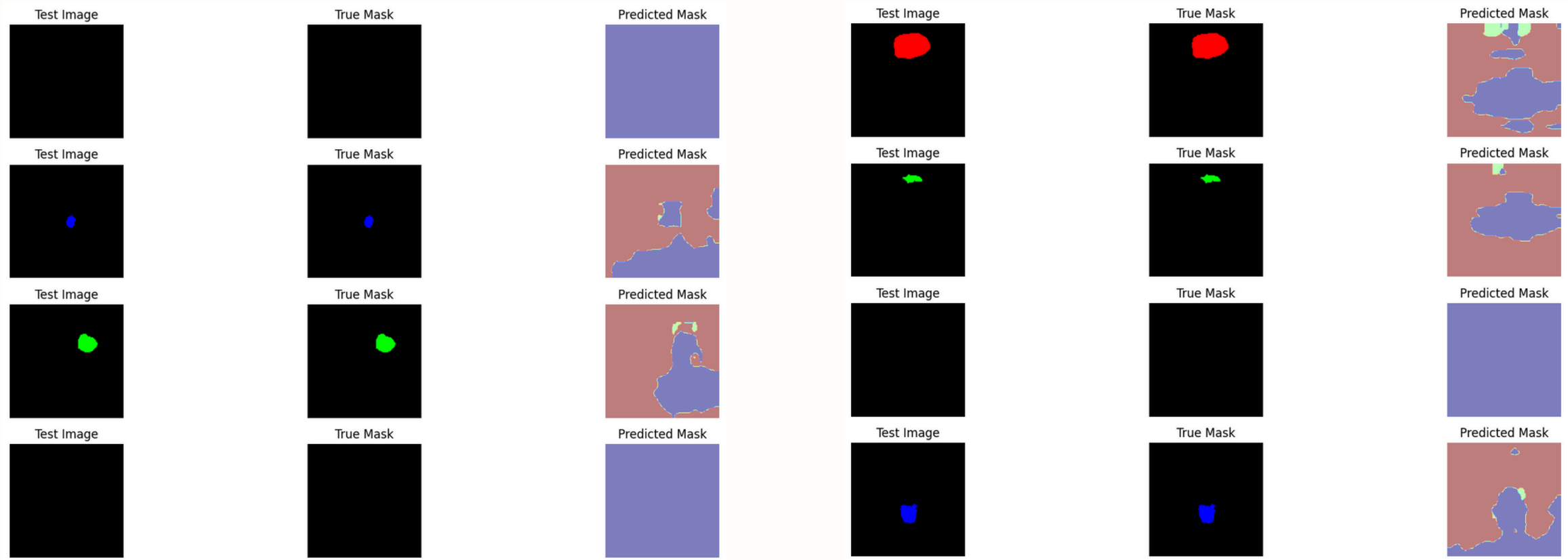
04. Segmentation Model

Results Obtained



04. Segmentation Model

Results Obtained



Test Accuracy: 43.73%

05. Generated Reports for Clinicians

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05. Generated Reports for Clinicians

Both Models Output the Same Prediction

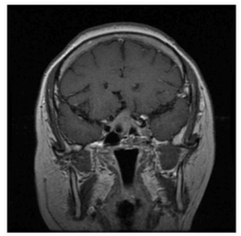
Brain Tumor Prediction Report

Patient Name: CHAN Tai Man

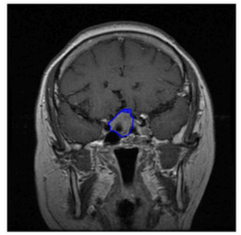
Prediction Result: Pituitary Tumor

**** This prediction result has a high confidence level. However, it is always advisable to consult with a qualified medical professional for a comprehensive evaluation.***

Patient's MRI Image:



Predicted Diagnosis MRI Image:



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05. Generated Reports for Clinicians

Models Output the Different Predictions

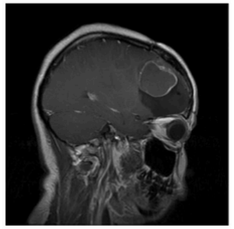
Brain Tumor Prediction Report

Patient Name: CHAN Tai Man

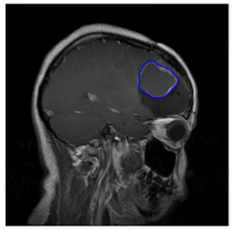
Prediction Result: Glioma Tumor

**** The prediction results are inconsistent. It is important to consult a qualified medical professional for a thorough evaluation and diagnosis to confirm the findings.***

Patient's MRI Image:



Predicted Diagnosis MRI Image:



Prepared by Juin Tan

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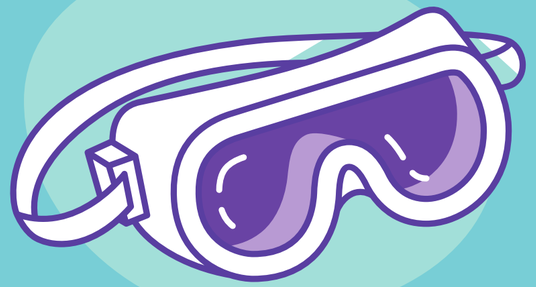

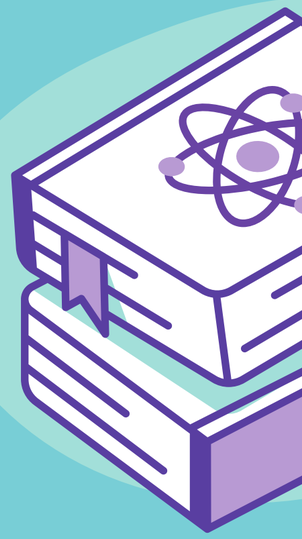

THANK YOU