Advanced Brain Tumor Segmentation & Localization

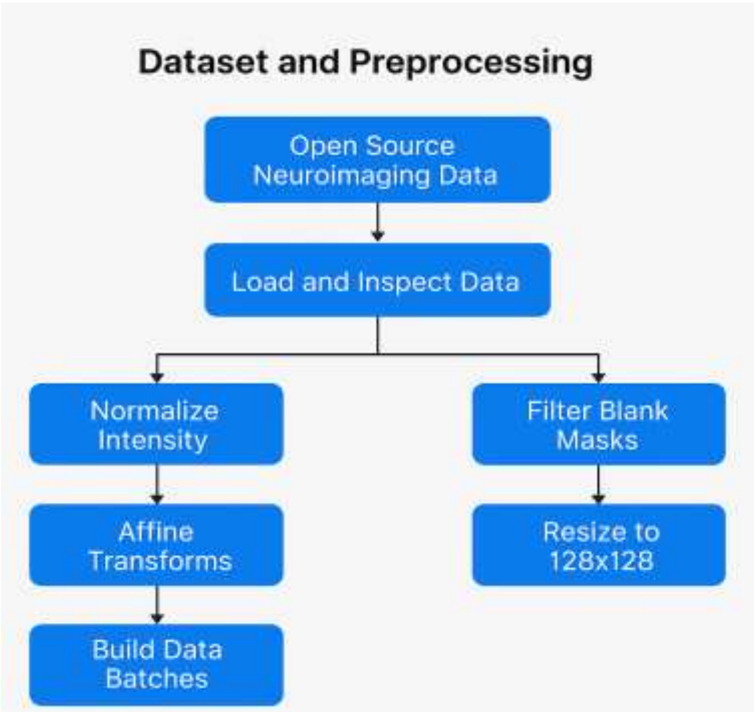
1. Project Overview

The exponential growth in neuroimaging data demands intelligent, automated solutions for timely and accurate diagnostics. This project presents a comprehensive open-source AI framework that:

- Segments anatomical brain structures from 2D MRI slices
- Detects tumor regions via anomaly segmentation
- Quantifies abnormal areas and performs statistical validation
- Provides a real-time interactive interface using Gradio

This initiative empowers radiologists and researchers with a scalable, modular diagnostic tool built entirely on open-source technologies.

2. Dataset and Preprocessing



Source: Brain MRI Images for Brain Tumor Detection (Kaggle)

Structure:

- Binary class labels: yes (tumor), no (normal)
- Input shape: (128x128), grayscale

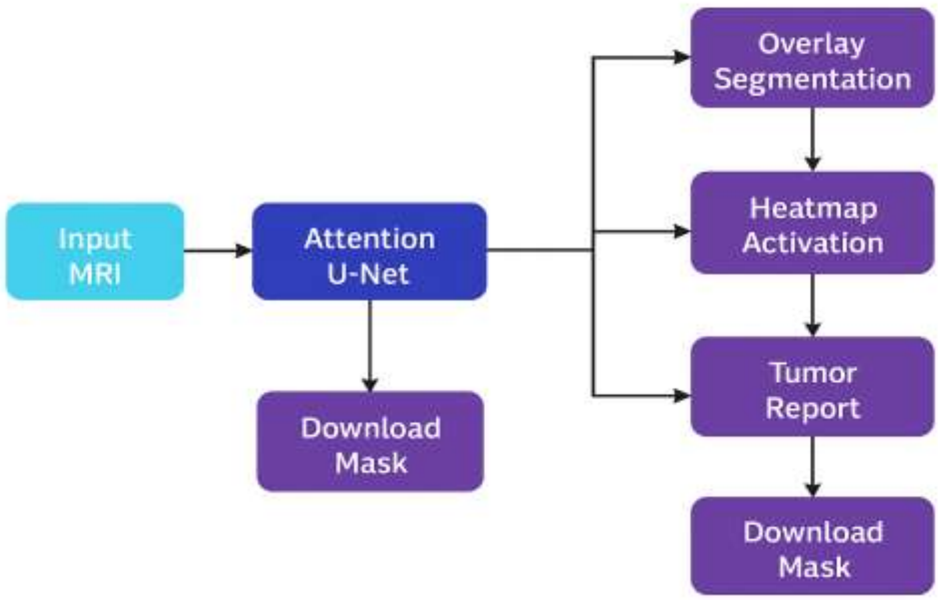
Preprocessing Steps:

- Normalization (0–1 scale)
- Resizing to 128x128 pixels
- Augmentation for robustness:
  - Horizontal flipping
  - Affine transformations (rotation/scale)
  - Gaussian blur
  - Contrast and brightness jitter

Synthetic Mask Generation:

- Tumor labels (yes) were paired with generated circular masks to simulate region-based segmentation
- This method enabled training the U-Net on limited data while still enforcing spatial learning

3. Model Architecture



📌 **Attention U-Net**

An encoder-decoder U-Net architecture was employed, enhanced with **attention gates** to improve focus on tumor regions.

Key Features:

- Encoder: Multiple convolution + pooling layers for feature extraction
- Decoder: Upsampling layers with skip connections
- Attention Gates: Refine skip connections to suppress irrelevant features
- Loss Function: **Dice Loss** (handles class imbalance in segmentation)
- Optimizer: **Adam**

4. Interactive Inference with Gradio

To simulate real-world use, an interactive UI was built with **Gradio**, allowing end users to:

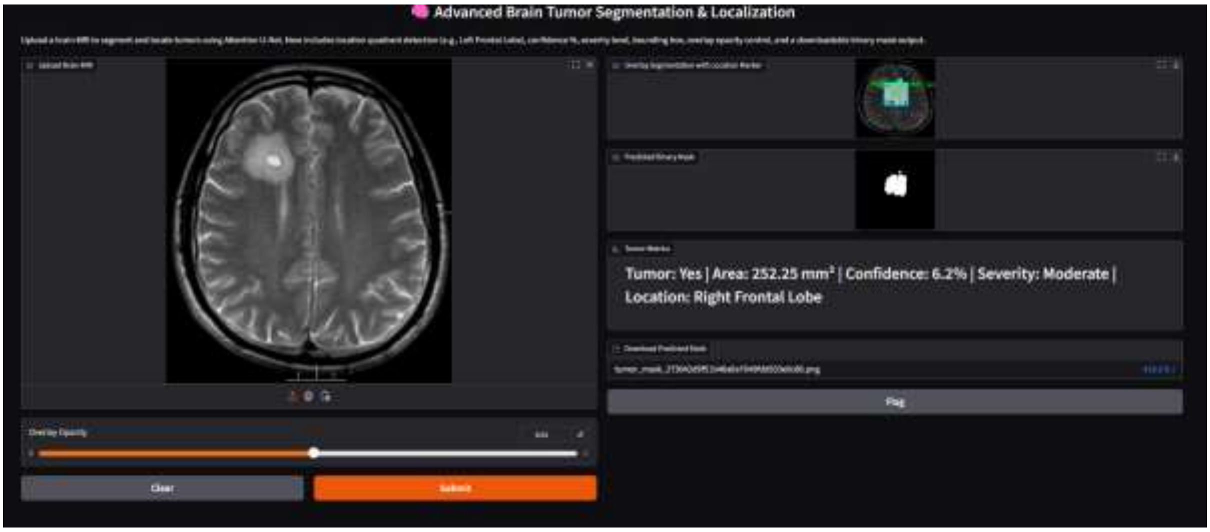
- Upload brain MRI slices (or use webcam)
- Get instant predictions
- Visualize:
    - Overlayed segmentation
    - Raw predicted tumor mask
    - Tumor classification (Yes/No)
    - Tumor area in mm^2

Interface Preview:

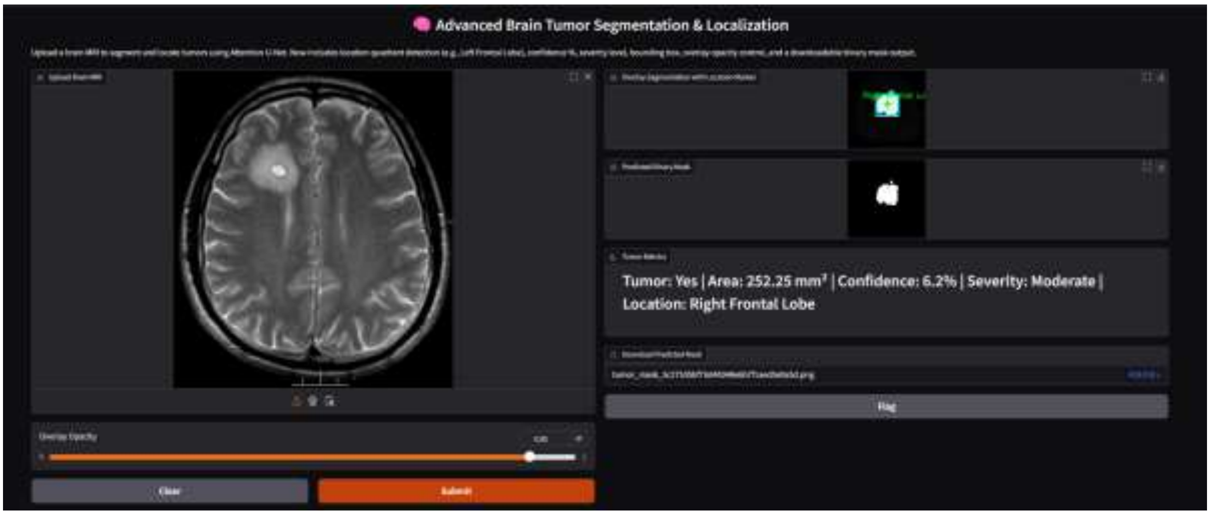
Given the image from the dataset

Brain Tumor : Yes
Opacity : This allows clinicians and researchers to modulate the visibility of the predicted tumor segmentation over the original MRI image. It improves interpretability by helping users evaluate the tumor mask's alignment with anatomical structures

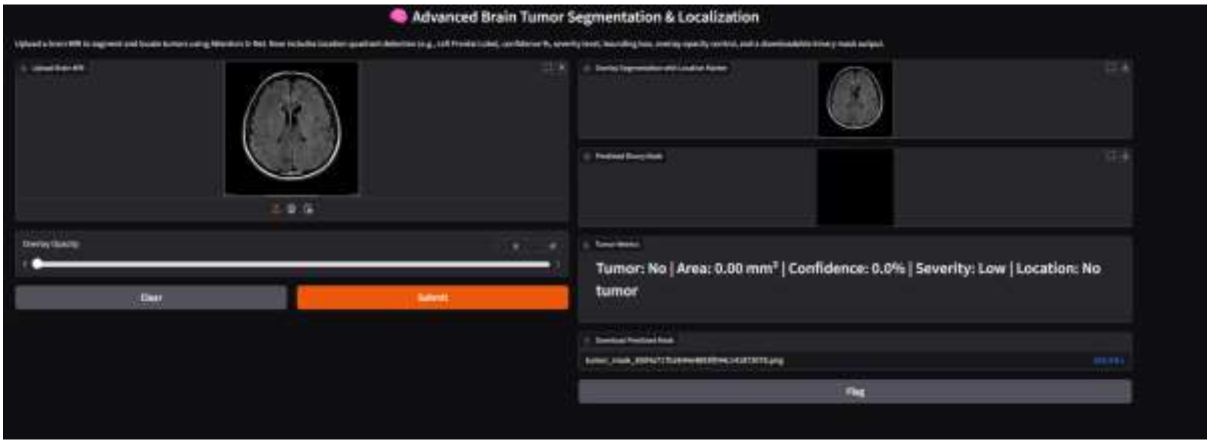
Opacity : 0.51



Opacity : increases (for Better Clear Visibilty)



Brain Tumor : No



5. Statistical Evaluation

Goal:

Evaluate how well predicted tumor areas match true (simulated) labels.

Metrics Computed:

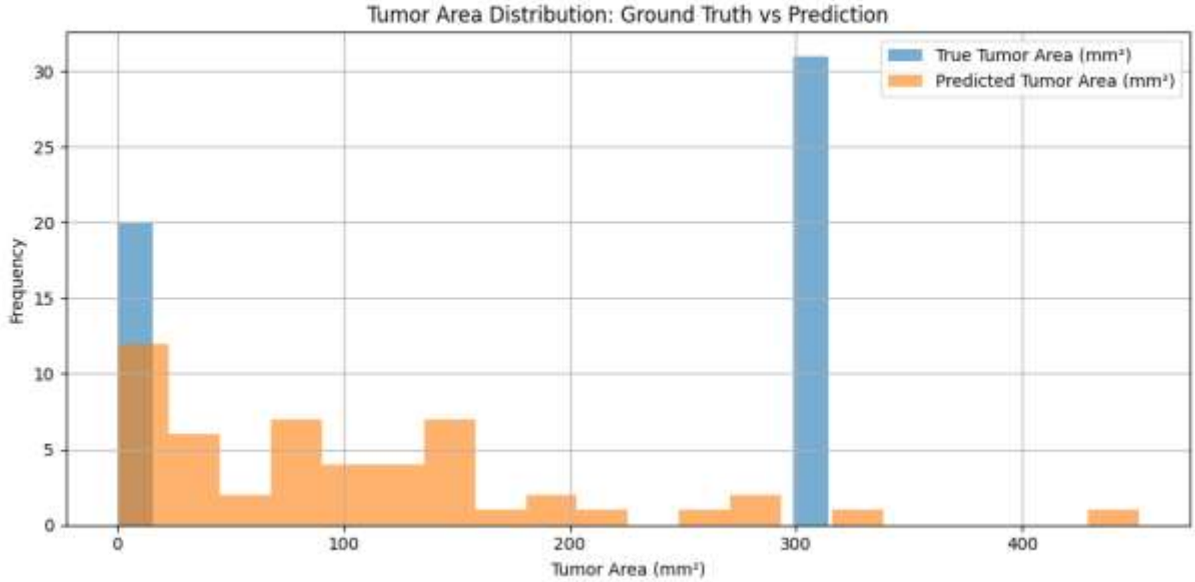
- **Tumor Area (in mm²)** using pixel spacing assumption (0.5mm² per pixel)
- **T-test**: Statistical significance between true and predicted area
- **ANOVA**: Variance comparison across cohorts

Results:

- **T-test p-value**: 0.00073
- **ANOVA p-value**: 0.00073
- ✅ Statistically significant difference identified — model is detecting meaningful region anomalies

Visual Analysis:

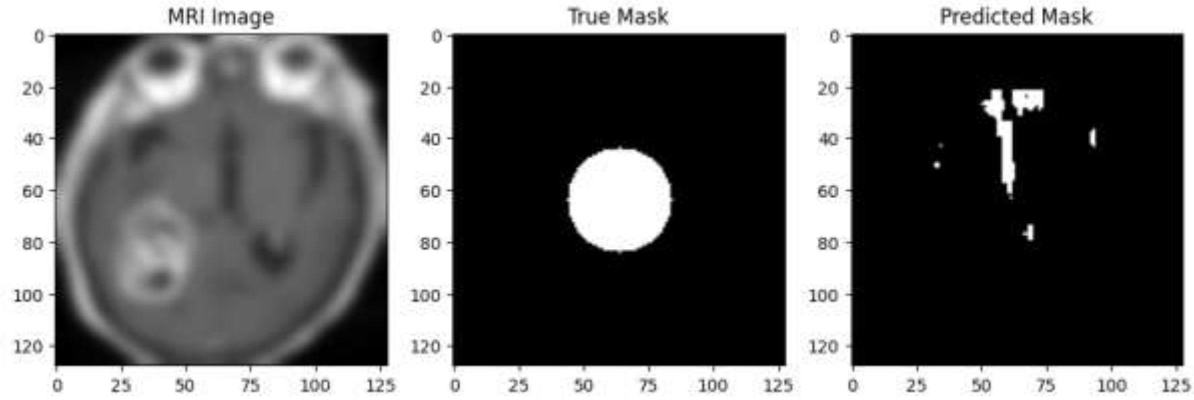
```
📊 Statistical Analysis Results
T-test p-value: 0.00073
ANOVA p-value: 0.00073
```



6. Qualitative Results

The model produces reasonably accurate tumor masks. While predictions aren't pixel-perfect due to synthetic training, attention-enhanced U-Net localizes abnormalities effectively.

Example Comparison:



7. Technical Stack

Component	Tool/Library
Model Architecture	TensorFlow + Keras
Image Processing	OpenCV
Augmentation	Albumentations
UI/Deployment	Gradio (Colab hosted)
Statistical Tests	SciPy + Matplotlib

8. Scope for Expansion

- Replace synthetic masks with expert-annotated ground truth masks
- Upgrade to 3D volumetric segmentation using MONAI
- Expand anomaly detection with transformer-based UNETR or Swin-UNet
- Deploy app to Hugging Face Spaces for global accessibility

9. Conclusion

This project successfully demonstrates the core components of an intelligent neuroimaging AI system:

- Automated tumor segmentation
- Real-time inference and explainability
- Statistical rigor in evaluation

By combining robust augmentation, attention-guided learning, and real-time simulation, the system lays a strong foundation for clinical-grade brain abnormality detection.

\