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A DIAGNOSTIC APPROACH FOR BRAIN TUMOR SEGMENTATION AND CLASSIFICATION IN BRAIN MRI

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Abstract - *Brain tumors are abnormal cell growths that disturb neurological functions and demand early detection. Manual delineation of tumors in MRI by radiologists is time-consuming and prone to human error. This work presents a deep-learning-based system for automatic brain tumor segmentation and classification using multi-modal MRI (T1, T2, T1ce and FLAIR) from the BraTS dataset. A 3D SegResNet, a residual encoder–decoder network, is trained with a combined Dice and cross-entropy loss to produce three tumor sub-regions: necrotic core, edema and enhancing tumor. The resulting tumor mask is passed to a rule-based classifier that labels each scan as Tumor or No Tumor. SegResNet is compared with a 3D U-Net over seven experiments, and the improved SegResNet reaches a best validation Dice score of 0.7591. The trained model is deployed as a Streamlit web application that displays segmentation results, confidence maps and quantitative analysis, and exports a downloadable PDF report.*

Key Words: Brain tumor, MRI, BraTS, SegResNet, U-Net, Dice coefficient, deep learning, Streamlit.

1. INTRODUCTION

Brain tumors are abnormal cell growths in the brain that affect neurological functions and require early detection. Magnetic Resonance Imaging (MRI) is commonly used for brain tumor diagnosis because of its detailed imaging of brain tissues. However, manual tumor detection by radiologists is time-consuming and may lead to human error. This project uses SegResNet for tumor segmentation and uses the resulting tumor mask for classification, so that brain tumor detection is automated end to end.

2. LITERATURE SURVEY

Recent work on automated brain tumor analysis is summarised in Table-1. Reviews of deep-learning segmentation on multi-modal MRI cover models, datasets and evaluation practice [4, 8], and several studies target detection and classification with CNN and machine-learning pipelines [3, 6, 7]. Pooling-based and ResNet50/CBAM-based U-Net variants improve segmentation quality [5, 9]. Attention-based and residual U-Net variants improve segmentation of small tumor regions at the cost of higher complexity [2, 12]; hybrid CNN–SVM models give high classification accuracy but no pixel-level localisation [10]; classical FCM/FCN–SVM pipelines are fast and effective on small datasets but cannot capture complex tumor patterns [1, 11]; and plain U-Net pipelines are fully automatic but depend on dataset quality and size [13].

Table -1: Summary of the literature survey

Paper / Year	Methodology	Advantages	Disadvantages
ARU-Net, Siddiqui et al. (2025)	Hybrid U-Net with spatial and channel attention, feature fusion and regression based output; BraTS.	Captures important tumor features; reduces noise; more stable than U-Net.	Higher computational cost and complexity; needs larger datasets.
Hybrid 3D CNN, Gholami (2025)	3D CNN with SVM, TSO optimisation and fuzzy weighting for classification.	Efficient hybrid; reduced computational load; high classification performance	Classification only; no pixel-level tumor localisation
FCM–SVM, Alqhtani et al. (2024)	Fuzzy C-Means segmentation, SVM classification, CLAHE pre-processing; ~98% accuracy Dice ~0.96.	Computationally efficient; works for smaller datasets.	Limited ability to capture complex tumor patterns.
Attention Residual UNet, Seeja and Naqvi (2024)	Residual connections and attention modules in U-Net for multi-modal MRI.	Better for small and subtle tumor regions.	Longer training time; more tuning required.
U-Net CNN, Mostafa and Rajendran (2023)	Encoder–decoder pixel-wise segmentation with normalisation.	Fully automated pipeline; suitable for structured datasets.	Depends on dataset quality; may not generalise to complex tumors.

3. AIM AND OBJECTIVES

The aim of this project is to study and implement a deep-learning-based system for automatic brain tumor segmentation and classification using MRI images. The objectives are:

1. To study various techniques for brain tumor segmentation and classification using MRI images.
2. To design and implement a deep-learning-based segmentation model for accurate tumor region extraction.
3. To develop a tumor-mask-based classification model for detecting and classifying tumor presence from segmented MRI images.
4. To analyse and evaluate the performance of the proposed system using metrics such as the Dice coefficient and accuracy.

4. DATASET

The dataset is obtained from the BraTS (Brain Tumor Segmentation) collection, which contains MRI scans of real patients. It consists of approximately 365 subject folders, each representing one patient case, and each folder holds four MRI modalities:

- **T1-weighted:** shows anatomy.
- **T2-weighted:** identifies abnormal fluid regions.
- **T1ce (contrast-enhanced):** detects the active tumor region.
- **FLAIR:** detects tumor boundaries.

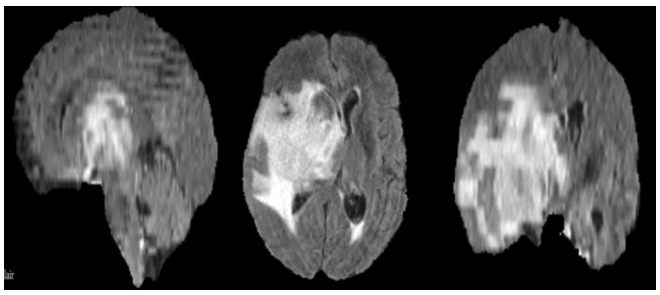


Fig -1: Sample MRI images from the dataset used in this project

5. METHODOLOGY

The overall pipeline is shown in Fig-2. A multi-modal MRI volume is pre-processed, segmented by SegResNet, converted to a binary tumor mask, and classified as Tumor or No Tumor; the final output can be downloaded as a PDF report. The steps of the method are as follows.

1. MRI input. Multi-modal MRI (T1, T2, T1ce, FLAIR) is represented as $I(x, y, z) \in \mathbb{R}^{H\times W\times D}$, where $I(x, y, z)$ is the voxel intensity and H, W, D are the height, width and depth.

2. Pre-processing. Resizing, normalisation, intensity scaling and augmentation improve data quality:

$$I_{norm} = \frac{I-\mu}{\sigma} \qquad (1)$$

where μ is the mean intensity and σ the standard deviation.

3. Segmentation. A 3D U-Net / SegResNet performs voxel-wise tumor detection. A CNN extracts features such as edges and tumor regions through 3D convolutions, and multi-class tumor regions (core, edema, enhancing) are produced, $Y \in \mathbb{R}^{3\times H\times W\times D}$.

4. Probability and thresholding. A sigmoid converts the outputs to probabilities, $P = \sigma(Y)$, and a binary tumor mask is generated; the same 0.5 threshold marks each pixel as tumor region or no tumor region:

$$\hat{Y} = \begin{cases} 1, & P > 0.5 \\ 0, & \text{otherwise.} \end{cases} \qquad (2)$$

5. Loss function. Dice loss improves segmentation accuracy and is combined with cross-entropy:

$$\text{Dice} = \frac{2\sum P_{ij}G_{ij}}{\sum P_{ij}+\sum G_{ij}}, \quad \text{Dice loss} = 1 - \text{Dice} \qquad (3)$$

where P_{ij} is the predicted value and G_{ij} the ground truth.

6. Classification and output. The rule-based classifier uses the tumor mask to label the scan as Tumor or No Tumor, and the result is exported as a report.

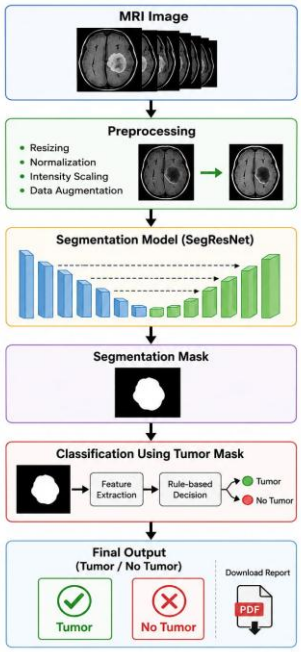
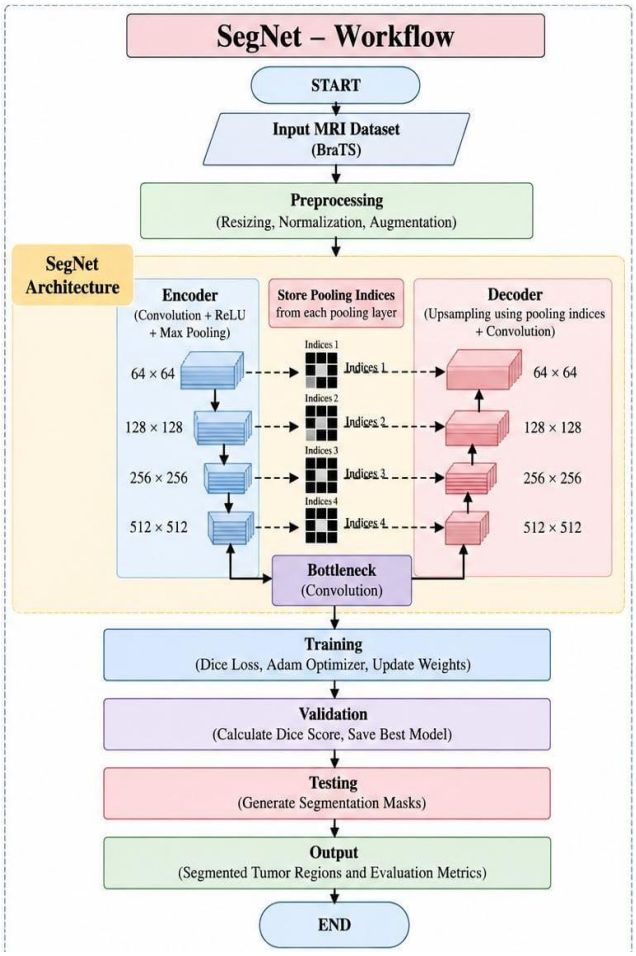


Fig -2: Block diagram of the proposed system

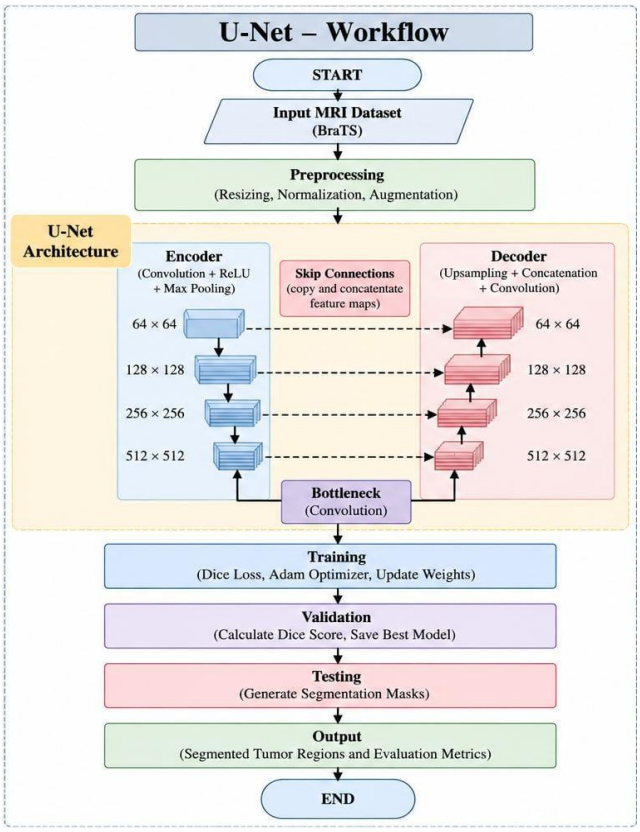
6. NETWORK ARCHITECTURES

SegResNet. SegResNet processes the MRI data as 3D volumes, so it captures spatial information across the whole brain. It takes four MRI modalities as input and combines their complementary information. A residual encoder–decoder architecture extracts deep features and reconstructs detailed segmentation maps, and the network produces three output channels: necrotic core, edema and enhancing tumor. It is trained with a combined Dice and cross-entropy loss, which improves the overlap between predicted and ground-truth regions, and the best model is selected on validation Dice. The workflow is shown in Fig-3a.

U-Net (baseline). The U-Net baseline also processes 3D brain MRI volumes with four modalities (t1.nii, t1ce.nii, t2.nii, flair.nii) and generates three output channels for the BraTS task (edema, necrotic core, enhancing tumor). It is trained with Dice loss, which measures the overlap between predicted and ground-truth segmentation. During validation the Dice score is computed and the best-performing model is kept (Fig-3b).



(a) SegResNet



(b) U-Net

Fig -3: Workflows of (a) SegResNet and (b) the U-Net baseline

7. RESULTS AND DISCUSSION

7.1 U-Net versus SegResNet

Seven experiments with different training sizes, validation sizes and epochs were run for both models (Table-2). SegResNet improves steadily as the training set and number of epochs grow, reaching its best Dice of 0.7591 with 120 training cases, 30 validation cases and 60 epochs, whereas U-Net reaches 0.7100 under the same setting. Fig-4 compares the two models.

Table -2: SegResNet and U-Net experiment results (validation Dice)

No	Train size	Val size	Epoch	SegResNet Dice	U-Net Dice
1	50	10	15	0.494900	0.40490
2	20/50†	10	45	0.681324	0.52300
3	50	30	20	0.653900	0.62390
4	80	20	25	0.462150	0.42900
5	100	30	35	0.653805	0.62000
6	100	30	40	0.698276	0.66000
7	120	30	60	**0.759117**	0.71000

†Training size is 20 for SegResNet and 50 for U-Net in the original tables; please verify which is correct.

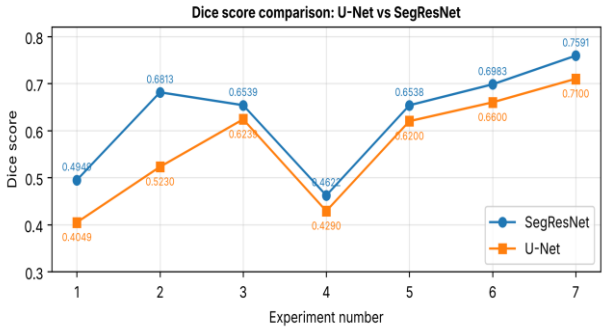


Fig -4: Dice score comparison: U-Net vs SegResNet (plotted from Table-2)

7.2 Segmentation Quality

Fig-5 compares the ground truth with the predicted segmentation. The predicted mask closely matches the ground truth, the sub-regions (NCR, ED, ET) are correctly identified, minor differences appear only at tumor edges, and the confidence heatmap shows high confidence inside the tumor.

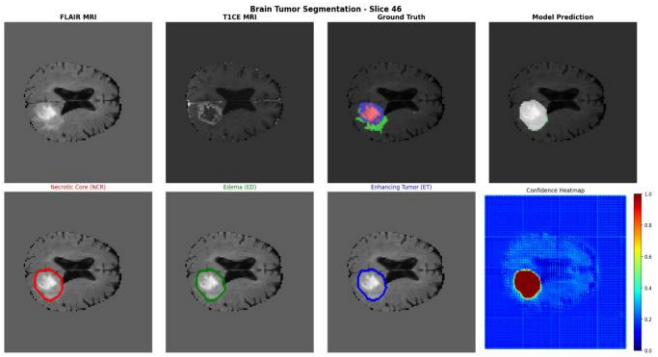
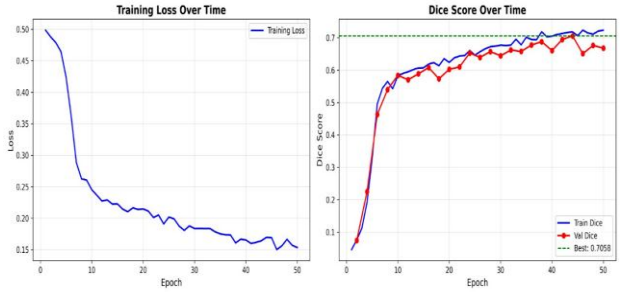


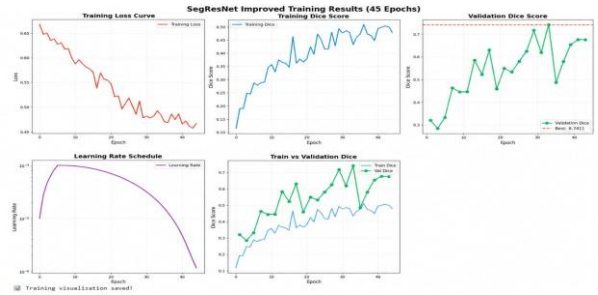
Fig -5: Comparison between ground truth and predicted tumor segmentation

7.3 Training Behaviour

The training loss decreases smoothly while the Dice score rises gradually, and training and validation Dice stay closely aligned, indicating minimal over-fitting (Fig-6). Learning-rate scheduling stabilises training, and the best Dice reaches 0.70–0.76 (Fig-6b).



(a) Trend of training loss reduction and Dice score improvement over time

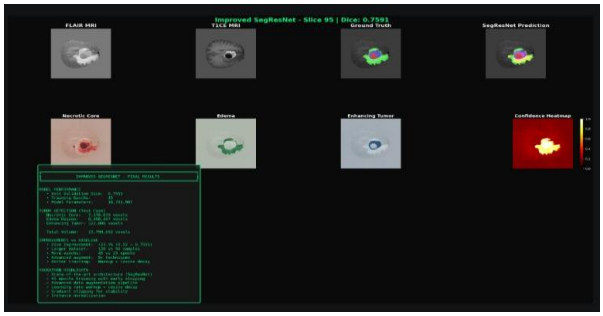


(b) Additional training performance metrics: Dice score and learning rate

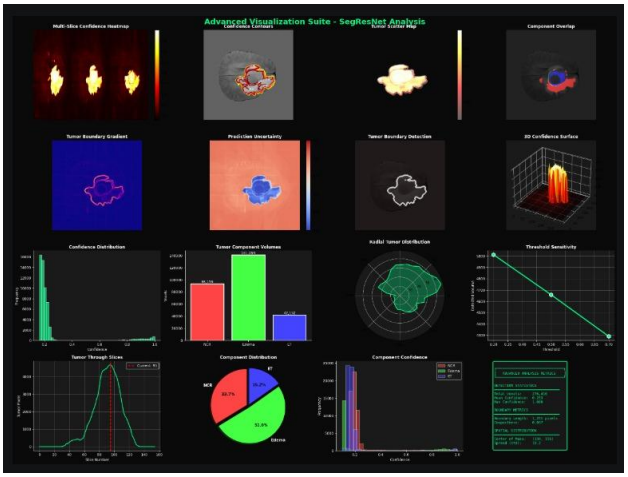
Fig -6: Training behaviour of SegResNet

7.4 Improved SegResNet and Advanced Analysis

With a larger dataset (120 vs. 50 samples), more epochs, advanced augmentation, learning-rate warm-up with cosine decay, gradient clipping and instance normalisation, the improved SegResNet reaches a validation Dice of 0.7591 (Fig-7a). Advanced visualisations (Fig-7b) include multi-slice confidence heatmaps, confidence contours, prediction uncertainty, tumor boundary gradient and detection, a 3D confidence surface, threshold sensitivity, tumor volume through slices, component volume and confidence distributions, and summary statistics.



(a) Visualization of improved SegResNet segmentation results



(b) Advanced SegResNet analysis (confidence, uncertainty, boundary, 3D surface, distributions, threshold sensitivity and summary statistics)

Fig -7: Improved SegResNet results and advanced analysis

8. STREAMLIT APPLICATION AND CASE STUDIES

Streamlit is an open-source Python framework for building interactive web applications for machine learning and data science. It is used here to turn the trained model into a simple interface between the user and the network: the user uploads a medical image (PNG, JPG, JPEG, NII or GZ, up to 200 MB), and the application displays the segmentation results, tumor boundaries, confidence maps and analysis graphs (Fig-8).

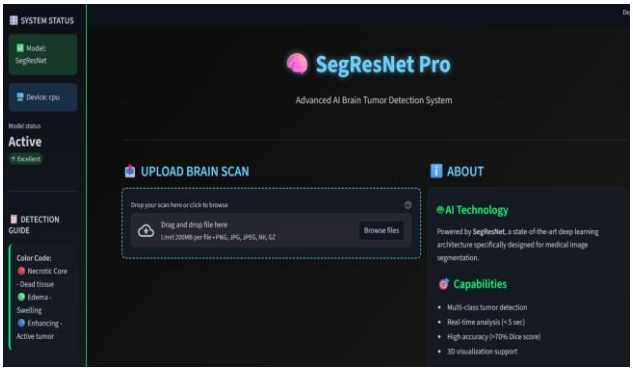
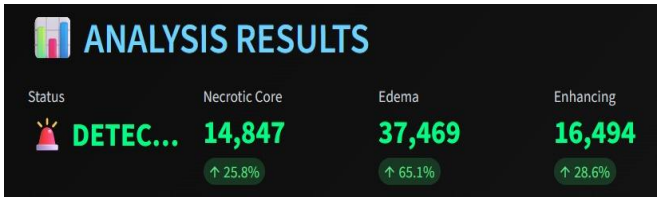


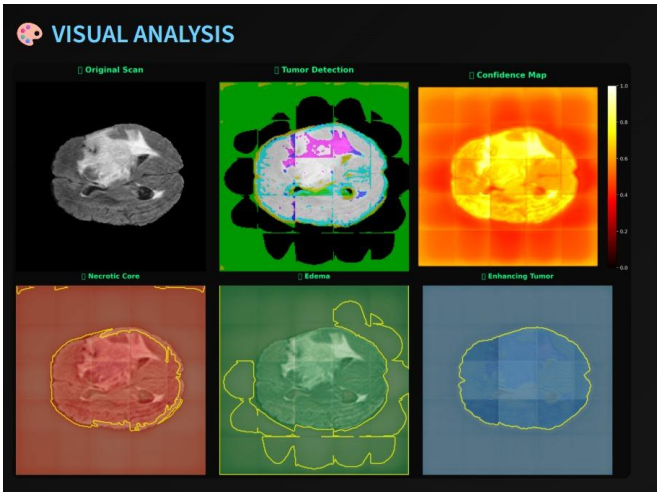
Fig -8: Brain tumor detection system interface

8.1 Tumor Case

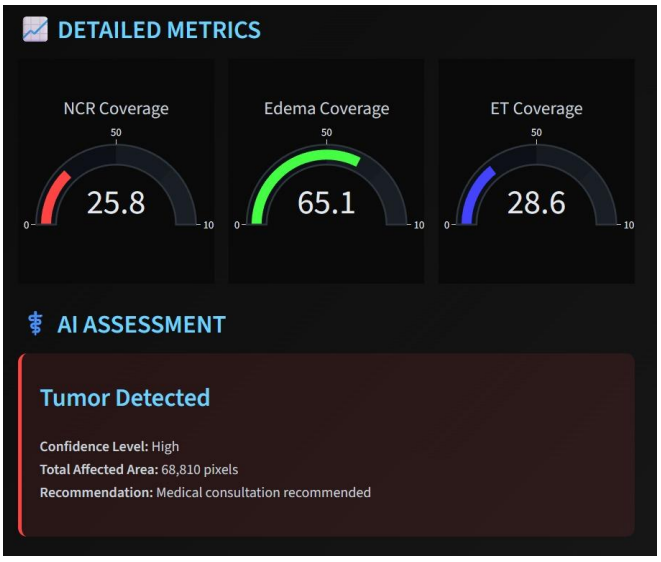
For a tumor scan the application reports the pixel counts and percentages of necrotic core (14,847; 25.8%), edema (37,469; 65.1%) and enhancing tumor (16,494; 28.6%), and the AI assessment returns "Tumor Detected" with high confidence, a total affected area of 68,810 pixels and a recommendation for medical consultation (Fig-9).



(top) Quantitative analysis



(a) Visual analysis of brain tumor segmentation and detection



(b) AI-based tumor assessment and detailed metrics

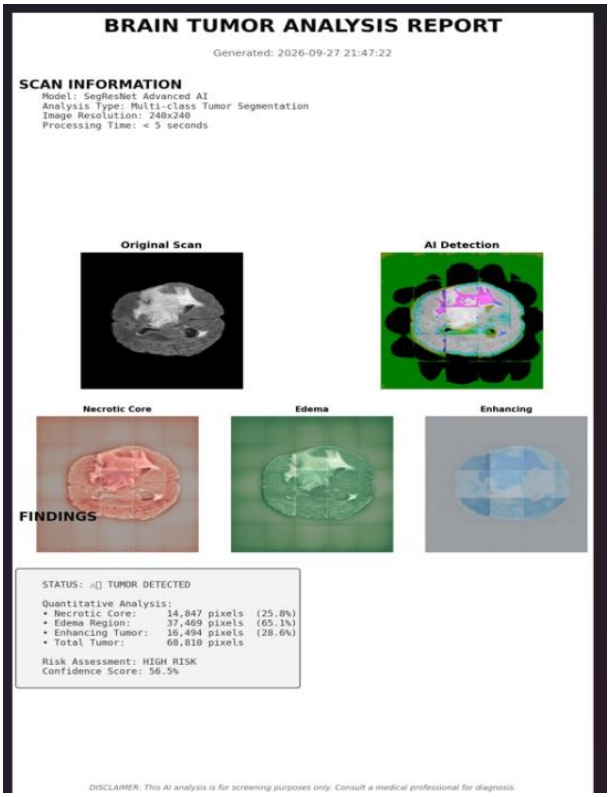
Fig -9: Tumor case: quantitative analysis (top), visual analysis (a) and AI assessment (b)

8.2 Analysis Report

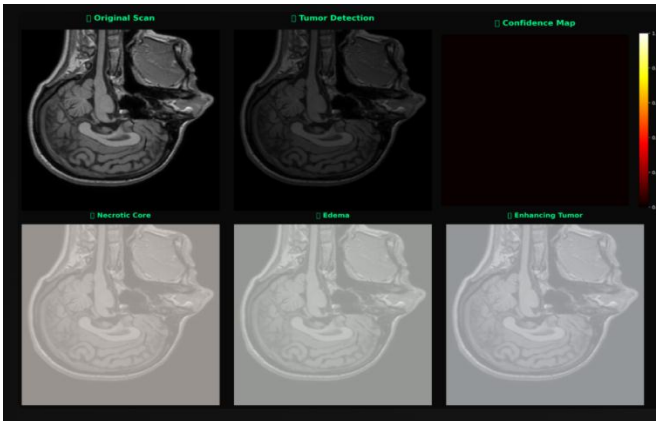
The user can download the analysis as a PNG or a full PDF report containing scan information, the original scan, AI detection, the three sub-region overlays, quantitative findings, a risk assessment and a screening disclaimer (Fig-10a).

8.3 Healthy Brain Case

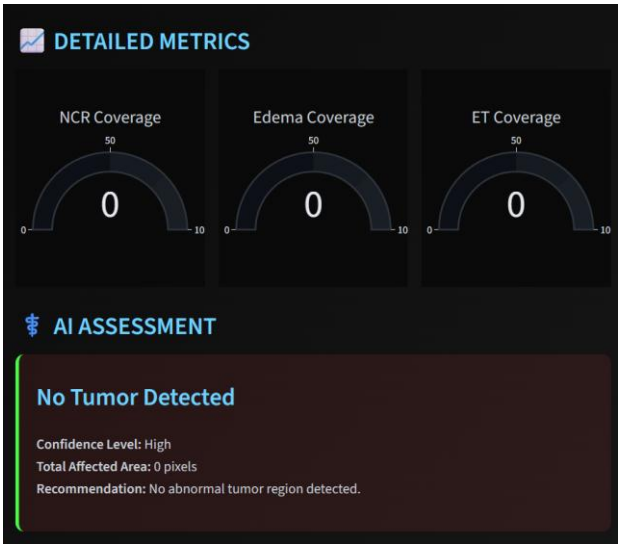
For a healthy scan all three sub-regions report 0 pixels (0.0%), the status is “Clear”, and the assessment reads “No Tumor Detected” with no abnormal region (Fig-10b–d).



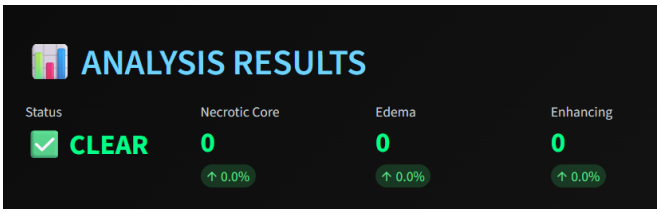
(a) PDF report (tumor case)



(b) Healthy case: visual analysis



(c) Healthy case: assessment and metrics



(d) Healthy case: quantitative analysis

Fig -10: Downloadable PDF report (a) and healthy brain case (b–d)

9. CONCLUSION

This project implements a deep-learning-based system for brain tumor segmentation and classification in MRI. A 3D SegResNet segments necrotic core, edema and enhancing tumor from four MRI modalities, and the tumor mask drives a Tumor / No Tumor decision. In the seven-experiment comparison, SegResNet outperformed U-Net in the largest setting, with a best Dice of 0.7591 versus 0.7100, and training and validation curves show minimal over-fitting. The model is packaged as a Streamlit application with visual analysis and a downloadable PDF report. The tool is intended for screening support only, and a medical professional must be consulted for diagnosis.

9.1 Future Scope

Future work includes training on larger and more diverse datasets, adding attention modules and residual-attention variants to improve small-tumor segmentation, and extending the classifier to tumor types and grades beyond the present binary decision.

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