BrainDx : AI-Powered Brain Tumor Detection with Precision and Speed

MEMBERS:

Kushal Debnath
Gayathri Reddy Epur
Anand loomba
Sreerama Monisha

SRI SRI UNVERSITY

FACULTY OF ENGINEERING & TECHNOLOGY

PROJECT REPORT

ON

Brain Tumor Detection

Using Deep Learning

Bachelor Of Computer Science and Technology

(AIML)

SUBMITTED BY:

1. Kushal Debnath(FET-BAML-2022-26-005)
2. Anand Loomba(FET-BAML-2022-26-006)
3. Gayathri Reddy Epur(FET-BAML-2022-26-018)
4. Sreerama Monisha(FET-BAML-2022-26-004)

INDUSTRY EXPERT

Dr. Srinivasan

GUIDED BY

Dr. Satyajit Pattnaik

(SME IBM) (Associate Professor)
(Sri Sri University)

Certificate of Submission

This is to certify that Kushal Debnath, Anand Loomba, Gayathri Reddy Epur and Sreerama Monisha enrolled in B.Tech Computer Science and Engineering at Sri Sri University have successfully completed and submitted their major project titled **"*Brain Tumor Segementation using Deep Learning*"** as part of their academic curriculum. The project was submitted on 15th of April,2025.

Throughout the duration of this project, the students have demonstrated a commendable understanding of the subject matter and have exhibited exceptional skills in research, analysis, and presentation.

We acknowledge the effort and dedication put forth by the students in completing this project and commend their commitment to academic excellence.

Signature of Internal Examiner

Signature of External Examiner

ACKNOWLEDGEMENT

We would like to express our sincere gratitude to all those who contributed to the success of this project. First and foremost, we extend our heartfelt thanks to the management and Experts team for their continuous support and encouragement throughout the project.

We are immensely grateful to our team members for their dedication, hard work, and collaboration, which played a pivotal role in developing and implementing the predictive maintenance model. Their expertise, creativity, and commitment have been instrumental in achieving our project objectives.

We would like to acknowledge the invaluable support and guidance provided by our mentor, **Dr. Satyajit Pattnaik** and subject matter experts, Dr. Srinivasan. Their insights, feedback, and expertise have significantly enriched the project and enhanced its impact.

We extend our appreciation to all stakeholders, including our industry partners IBM, for their valuable inputs, data, and resources that contributed to the success of the project. Their collaboration and cooperation have been essential in understanding industry requirements and implementing effective solutions.

Last but not least, we acknowledge the support of our families, friends, and colleagues who stood by us and provided encouragement and understanding throughout the project journey.

Thank you to everyone involved for their contributions, dedication, and commitment to excellence, making this project a success.

ABSTRACT

Brain tumor detection is a critical task in medical imaging, as early and precise diagnosis can significantly improve patient survival rates and treatment outcomes. Magnetic Resonance Imaging (MRI) is the most widely used technique for brain tumor detection due to its ability to produce high-resolution images of brain structures. However, manual diagnosis through MRI scans is time-consuming, prone to human error, and lacks real-time efficiency during surgical procedures. To address these challenges, this study focuses on developing a real-time deep learning-based tumor Detection model that accurately predicts the location and size of brain tumors, assisting doctors in making critical surgical decisions directly in the Operating Theater (OT).

The proposed approach integrates advanced deep learning YOLO which offer precise segmentation of tumors from MRI images. The key steps include image pre-processing, adaptive filtering, feature extraction, and image enhancement, ensuring improved accuracy and reliability. Unlike traditional machine learning methods, which require manual feature extraction and struggle with complex tumor variations, deep learning models learn directly from raw MRI data, enabling faster and more accurate tumor identification.

Despite advancements in brain tumor detection, existing models face challenges such as slow processing speeds, high computational costs, and lack of real-time applicability. This study aims to overcome these limitations by developing a lightweight and high-speed deep learning model optimized for real-time use in surgical environments. Literature surveys reveal that the highest Dice scores achieved are 94.63% (WT), 93.54% (ET), and 87.81% (TC), while the highest accuracy reported is 98.64% (using UNet++, DSM, and classifiers like SVM, RF, and MLP), highlighting the potential of deep learning in brain tumor segmentation. By providing precise tumor localization and segmentation in real-time, this research will help neurosurgeons perform more accurate and safer operations, reduce surgical risks, and enhance post-operative recovery. Ultimately, this work contributes to making brain tumor detection faster, more efficient, and highly reliable in clinical practice, revolutionizing neurosurgical procedures and patient care.

Overall,This project will make use of MRI and deep learning to enhance brain tumor detection and surgical precision. By developing a real-time segmentation model YOLO it will aim to accurately predict tumor location and size, assisting neurosurgeons during surgery.

CONTENTS

INTRODUCTION

1.1 What Are Brain Tumors and How Do They Affect Health?

Brain tumors are an abnormal and uncontrolled growth of cells in the brain. There has been an increase in incidences of brain tumors in all ages globally over the past few years. These tumors can be benign (non-cancerous) or malignant (cancerous), with varying sizes, locations, and severity. Malignant tumors typically develop quickly and infect neighboring brain tissues, causing major health risks. Brain tumors can start in the brain (primary tumors) or spread to other parts of the body (secondary or metastatic tumors). Primary brain tumors include gliomas, meningiomas, pituitary adenomas, and medulloblastomas, while secondary brain tumors occur when cancer from other organs, such as the lungs or breasts, spreads to the brain. According to many Brain Surgeon, the types of Brain tumor are more than 150 globally. A tumor alters normal brain activities, which can result in symptoms like persistent headaches, seizures, memory loss, difficulty speaking, vision issues, and cognitive impairment. The exact cause of brain tumors is not always clear, but factors such as genetic mutations, radiation exposure, and a family history of brain tumors may contribute to their development.

1.2.Why Is Early Detection of Brain Tumors So Important?

Early detection of brain tumors is crucial for improving patient survival rates and ensuring effective treatment. Since brain tumors can grow rapidly and affect critical brain functions, delayed diagnosis can lead to severe neurological damage, reduced treatment options, and lower chances of recovery. Detecting tumors in their early stages allows for timely medical intervention, which can help in choosing the most suitable treatment methods, such as surgery, radiation therapy, or chemotherapy, before the tumor becomes more aggressive. Additionally, early detection reduces the risk of irreversible brain damage, improves surgical precision, and enhances post-treatment recovery.

1.3.How Does MRI Help in the Diagnosis of Brain Tumors?

Magnetic Resonance Imaging (MRI) is the most widely used technique for detecting brain tumors due to its ability to produce high-resolution, detailed images of brain structures. MRI uses strong magnetic fields and radio waves to create clear and precise images of soft tissues, making it highly effective in identifying tumors, their location, and their effect on surrounding brain areas. Unlike CT scans or X-rays, MRI does not use ionizing radiation, reducing the risk of exposure-related complications. Furthermore, advanced MRI techniques, such as contrast-enhanced MRI and functional MRI (fMRI), provide deeper insights into tumor characteristics, helping doctors distinguish between benign and malignant tumors and plan the most appropriate treatment strategies. Its accuracy, non-invasive nature, and ability to detect even small abnormalities make MRI the gold standard for brain tumor diagnosis.

1.4. How Has Deep Learning Improved Brain Tumor Detection?

Deep learning, a subset of artificial intelligence, has revolutionized medical image analysis by enabling automated and highly accurate detection of abnormalities in MRI scans. Unlike traditional machine learning, which requires manual feature extraction, deep learning models learn patterns directly from raw images, making them particularly effective for complex visual data like brain MRIs. In traditional machine learning, radiologists and engineers must define specific features such as tumor shape, texture, or intensity, which can be time-consuming and prone to human bias. However, this approach often fails when tumors vary in size, shape, or contrast due to differences in imaging conditions.

To address these challenges, deep learning-based models such as YOLO (You Only Look Once), U-Net, and SegNet have been widely used for tumor detection and segmentation in MRI images. U-Net, a specialized convolutional neural network, is particularly effective for biomedical image segmentation due to its encoder-decoder structure, which captures both high-level and fine-grained details of the tumor. YOLO, on the other hand, is a real-time object detection algorithm that helps in locating and identifying tumors quickly within MRI scans. SegNet, another deep learning model, is optimized for pixel-wise segmentation, making it useful for delineating tumor boundaries with high precision. These models significantly outperform traditional machine learning methods by accurately detecting tumors, adapting to variations in image quality, and reducing the need for manual intervention. By leveraging such deep learning techniques, brain tumor detection has become faster, more accurate, and more reliable, ultimately improving diagnostic efficiency and treatment planning.

LITERATURE SURVEY

2.1 Existing Works

	Author	Year	Paper Title	Objective	Methodology	Results
1.	Fabian Isensee1, Paul F. Jager1, Peter M. Full1, Philipp Vollmuth 2 , and Klaus H.Maier-Hein	2020	nnU-Net for Brain Tumor Segmentation	The paper aims to improve brain tumor segmentation in the BraTS 2020 challenge by modifying nnU-Net with BraTS-specific postprocessing, region-based training, and data augmentation.	nnU-Net, Region-based training, Aggressive data augmentation, Postprocessing techniques, batch normalization and batch Dice loss	Dice Scores: WT: 88.95, TC: 85.06, ET: 82.03 HD95 values: WT 8.498, TC 17.337, ET 17.805
2.	Konstantinos Kamnitsas 12 , Enzo Ferrante1, Sarah Parisot1, Christian Ledig1, Aditya Nori2	2017	DeepMedic for Brain Tumor Segmentation	The objective of this research paper is to enhance DeepMedic 3D CNN with residual connections for brain tumor segmentation and evaluate its performance on BraTS 2015 and 2016 datasets, focusing on TC segmentation.	DeepMedic (3D CNN-based segmentation) Residual connections, CRF postprocessing , multi-scale processing.	Dice Scores: WT 91.4, TC 83.1, ET 79.4.
3.	Mohammad Havaeia,1, Axel Davyb, David Warde-Farleyc, Antoine Biardc,d, Aaron Courvillec , Yoshua Bengioc,	2016	Brain Tumor Segmentation with Deep Neural Networks	The objective of this research paper is to present an automatic brain tumor segmentation approach using CNNs, with a two-pathway design and cascaded framework to enhance accuracy and efficiency.	TwoPathCNN InputCascadeCNN LocalCascadeCNN MFCascadeCNN	Dice Scores: WT: 0.88 TC: 0.79 ET: 0.73

4.	Zachary Schwehr, Sriman Achanta	2024	Brain Tumor Segmentation Based on Deep Learning, Attention Mechanisms, and Energy-Based Uncertainty Prediction	To enhance brain tumor segmentation by proposing a region of interest detection algorithm for MRI data preprocessing. This aims to reduce input size, enable more data augmentations, use deep neural networks, and achieve high segmentation accuracy with uncertainty predictions.	Region of interest detection algorithm. U-Net, CNN autoencoder, Attention, Energy-based model, Test-time augmentations	Mean Dice scores of 84.55, 88.52, and 90.82 on BraTS 2019, 2020, and 2021 datasets respectively.
5.	Xi Guan, Guang Yang, Jianming Ye, Weiji Yang, Xiaomei Xu, Weiwei Jiang, Xiaobo Lai	2022	3D AGSE-VNet: An Automatic Brain Tumor MRI Data Segmentation Framework	Propose an automatic brain tumor segmentation framework (AGSE-VNet) to improve segmentation accuracy by integrating attention mechanisms and squeeze-excite modules.	AGSE-VNet : Squeeze and Excitation (SE) module, Attention Guide Filter (AG)	Accuracy : Dice Score: WT: 0.68 TC: 0.85 ET: 0.70
6.	Wentao Wu, Daning Li, Jiaoyang Du, Xiangyu Gao, Wen Gu, Fanfan Zhao, Xiaojie Feng, Hong Yan	2020	An Intelligent Diagnosis Method of Brain MRI Tumor Segmentation Using Deep Convolutional Neural Network and SVM Algorithm	Improve segmentation performance by integrating DCNN and SVM for more accurate classification of glioma regions in MRI scans.	Deep Convolutional Neural Network (DCNN) Support Vector Machine (SVM)	
7.	Hasnain Ali Shah, Faisal Saeed, Sangseok Yun, Jun-	2022	A Robust Approach for Brain Tumor Detection in	Fine-tune EfficientNet to improve brain tumor classification accuracy in MRI scans.	EfficientNet-B0, Data augmentation and transfer learning	Final Accuracy: 98.87%

	Hyun Park, Anand Paul, Jae-Mo Kang		Magnetic Resonance Images Using Finetuned EfficientNet			
8.	Shubhangi Nema, Akshay Dudhane, Subrahmanyam Murala, Srivatsava Naidub	2019	RescueNet - An Unpaired GAN for Brain Tumor Segmentation	This paper proposes *RescueNet*, a deep learning model using an unpaired GAN for brain tumor segmentation in MRI scans, enhancing performance without paired data.	RescueNet GAN-based training RescueWNet (WT), RescueCNet (TC), and RescueENet (ET)	Accuracy: Dice Score: WT: 94.63% TC: 85.6% ET:93.54%
9.	Amjad Rehman Khan, Siraj Khan, Majid Harouni, Rashid Abbasi, Sajid Iqbal, Zahid Mehmood	2021	Brain Tumor Segmentation Using K-Means Clustering & Deep Learning	This study presents a hybrid method combining K-means clustering for segmentation and fine-tuned VGG19 CNN for classification, with synthetic data augmentation to improve accuracy.	K-Means Clustering VGG19 CNN model Synthetic Data Augmentation transfer learning	Classification accuracy: Before DA: 90.03% After DA: 94.06%
10.	Huan Minh Luu, Sung-Hong Park	2021	Extending nn-UNet for Brain Tumor Segmentation	The paper modifies the nn-UNet framework for improved brain tumor segmentation by incorporating group normalization, larger networks, and axial attention in the decoder.	nn-UNet, 3D U-Net framework	Dice Scores: ET: 84.51, TC: 87.81, WT: 92.75 HD95: ET - 22.41, TC - 9.20, WT - 3.42
11.	Abhishta Bhandari, Jarrad Koppen, Marc Agzarian	2020	Convolutional Neural Networks for Brain Tumor Segmentation	This study explores CNNs for glioblastoma segmentation, showing improved consistency over manual methods and discussing	CNNs, Feature extraction via deep learning, Data augmentation, Watershed algorithm	Dice Scores: WT: 0.89 TC: 0.76 ET: 0.81

				future applications in radiomics.		
12.	J. Walsh, A. Othmani, M. Jain	2022	Using U-Net for Efficient Brain Tumor Segmentation	Proposes an optimized, lightweight U-Net architecture for segmenting brain tumors from MRI scans with minimal computational resources.	U-Net, 2D image conversion, Lightweight implementation	Pixel Accuracy: 99% Mean IoU: 89%
13.	Shengcong Chen, Changxing Ding, Minfeng Liu	2018	Dual-Force Convolutional Neural Networks for Accurate Brain Tumor Segmentation	The paper proposes a dual-force training strategy to improve feature learning in CNNs for brain tumor segmentation, extending DeepMedic to MLDeepMedic and introducing MLP-based post-processing for better accuracy.	Multi-Level DeepMedic CNN, U-Net, Hierarchical feature learning, Multi-Layer Perceptron (MLP)	Dice Scores: BraTS 2017: WT: 89.3 TC :73.88 ET: 73.46 BraTS 2015: WT: 85 TC: 70 ET: 63
14.	Khushboo Munir Fabrizio Frezza, Antonello Rizzi	2022	Deep Learning Hybrid Techniques for Brain Tumor Segmentation	This paper proposes hybrid deep learning techniques using modified U-Net architectures with inception modules for brain tumor segmentation, aiming to improve accuracy, sensitivity, and specificity in detecting gliomas.	Recurrent-Inception U-Net (MI-Unet) Depth-wise Separable MI-Unet Hybrid Recurrent-Inception U-Net Depth-wise Separable Hybrid Recurrent-Inception U-Net	Dice Coefficient :87.75% Sensitivity: 90.26% Specificity: 99.42%
15.	Mehrdad Noori, Ali Bahri, Karim Mohammadi	2020	Attention-Guided Version of 2D UNet for Automatic Brain	This paper introduces an attention-guided 2D U-Net with multi-view fusion for brain tumor segmentation,	Modified 2D U-Net with: Attention Mechanism (SE Blocks), Multi-View Fusion	Dice Scores: ET: 81.3% WT: 89.5% TC: 82.3%

			Tumor Segmentation	improving feature extraction and reducing model confusion.		
16.	Chandrakant M. Umarani, S.G. Gollagi, Shridhar Allagi, Kuldeep Sambrekar, Sanjay B. Ankali	2024	Advancements in Deep Learning Techniques for Brain Tumor Segmentation: A Survey	The paper proposes a deep learning framework integrating U-Net with self-attention mechanisms to improve accuracy, precision, and sensitivity in brain tumor segmentation.	U-Net++DSM (Deep Supervision Mechanism), TransU2-Net, F2-Net, DenseTrans, Caps-VGGNet Hybrid Model	U-Net++DSM Sensitivity: 98.59% Specificity: 98.64% Accuracy: 98.64% Dice Score: 98.02%
17.	Zhihua Liu, Lei Tong, Long Chen, Zheheng Jiang, Feixiang	2022	Deep Learning-Based Brain Tumor Segmentation: A Survey	The paper reviews deep learning-based brain tumor segmentation techniques, analyzing over 150 studies to highlight trends, challenges, and future directions.	DenseTrans, TransU2-Net	DenseTrans: Dice Score of 93.2% TransU2-Net: Dice Score of 88.17%
18.	Almetwally M. Mostafa, MohammedZakariah and EmanAbdullah Aldakheel,	2023	Brain Tumor Segmentation Using Deep Learning on MRI Images	The study develops an automated deep learning system using a CNN with U-Net sampling for classifying and segmenting brain tumors, including gliomas and pituitary tumors.	CNN, Deep CNN with U-Net, FCN	Overall validation accuracy: 98% Dice Coefficient: 0.9012 Mean IoU: 0.9123 Precision: 0.9923 Sensitivity: 0.9678 Specificity: 0.9988
19.	R.Karthika, Dr.A.Gopi Kannan	2023	Brain Tumor Segmentation with Deep Learning	The study presents ZNet, a deep neural network that enhances brain tumor segmentation using skip connections, data	SVM, Naïve Bayes Classifier, KNN, ZNet, CNN	ZNet: Accuracy: 87.54% F1-Score: 16.58%

				augmentation, and adversarial networks.		
20.	J. Harshini, K. Gayatri	2021	Brain Tumor Detection Using Deep Learning Framework	The study aims to improve brain tumor classification accuracy and efficiency using a two-pathway CNN architecture integrating local and global features.	Support Vector Machines (SVM) Random Forests Multi-Layer Perceptron (MLP)	Accuracy: 98.64% Sensitivity: 98.59% Specificity: 98.64%

2.2 Critical Findings

1.Dice Score:

- WT- 94.63% [8] | RescueNet(GAN-based) (Range~68%)
- ET- 93.54% [8] | RescueNet(GAN-based) (Range~63%)
- TC- 87.81% | nn-UNet (Range ~70%)

2.Accuracy: 98.64%[8] [UNet ++ DSM /SVM, RF, MLP] (Range ~87.54)

3.Validation Accuracy: 98%[18]

4.Pixel Accuracy: 99% [12]

5.Sensitivity: 98.59% [16] (Range ~ 90.26)

6.Specificity: 99.88% [18] (Range ~ 98.64)

7.Common Methods : CNN and its different like- DCNN, 3D CNN etc, U-Net, V-Net, R-Net, TransU2-Net, F2-Net, DenseTrans, RF, SVM etc…[20]

3. MOTIVATION

However, despite advancements in medical imaging, there are still research gaps that challenge efficient and accurate tumor detection, motivating the need for further study:

- Manual Diagnosis is Time-Consuming and Prone to Errors.
- Limitations of Traditional Machine Learning
- Less Work Done on Segmentation Methods.
- Existing Models Lack Real-Time Efficiency
- High Computational Cost and Lack of Lightweight Models

4. MATHEMATICAL ANALOGY

The application of deep learning for medical image analysis, specifically brain tumor detection, involves several mathematical and algorithmic concepts. Two powerful models, ResUNet (used for semantic segmentation) and YOLO (used for object detection), are applied in this project to accurately identify and localize tumors in brain MRI images. This section provides a detailed mathematical analogy that underpins the inner workings of these models.

4.1Mathematical Framework of YOLO (Object Detection)

YOLO (You Only Look Once) is an object detection model that identifies and localizes tumors by drawing bounding boxes around them. Unlike segmentation, YOLO detects what and where the object (tumor) is in a single forward pass.

4.1.1 Grid-based Prediction

YOLO divides the input image into an *S×SS \times S*S×S grid. Each cell predicts:

- Bounding box coordinates: *x,y,w,hx, y, w, h*x,y,w,h
- Confidence score: Probability that a tumor is present
- Class probabilities: For classification, if multiple tumor types are considered

*Output=(x,y,w,h,confidence,c1,c2,...,cn)\text{Output} = \left(x, y, w, h, \text{confidence}, c_1, c_2, ..., c_n\right)*Output=(x,y,w,h,confidence,c1 ,c2 ,...,cn)

Where:

- *(x,y)(x, y)*(x,y) are center coordinates of the box (relative to the cell),
- *w,hw, h*w,h are the width and height,
- *cic_i*ci are class scores for multi-class classification.

4.1.2 Intersection Over Union (IoU)

To evaluate detection accuracy, IoU (Intersection over Union) is computed:

*IoU=Area of OverlapArea of Union\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}*IoU=Area of UnionArea of Overlap

IoU compares the predicted bounding box with the ground truth and is used during both training and evaluation.

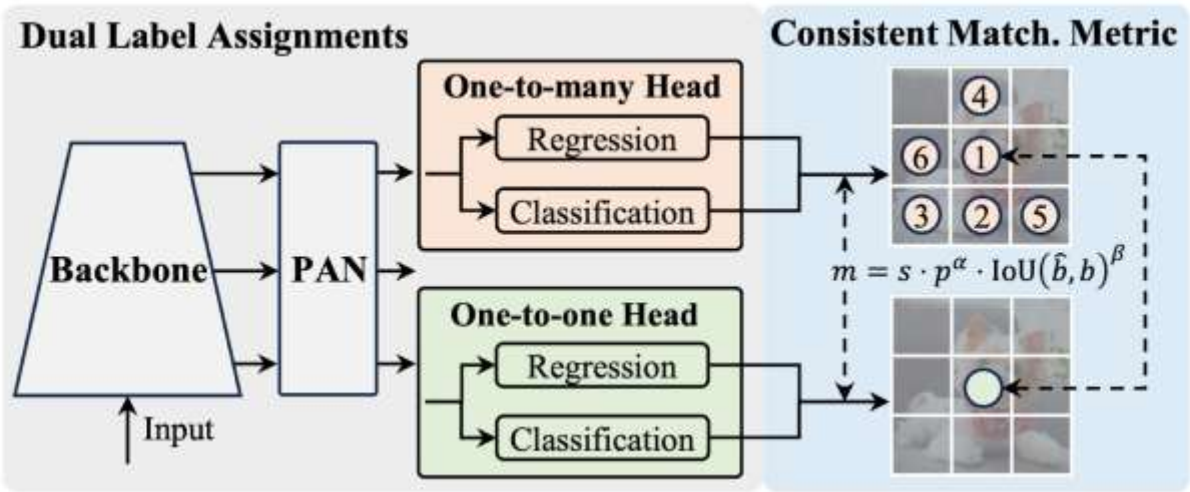
4.1.3 YOLO Loss Function

The total loss is a combination of multiple components:

*LYOLO=λcoord∑(x−x^)2+(y−y^)2+(w−w^)2+(h−h^)2+∑(conf−conf^)2+∑(class−class^)2\mathcal{L}_{\text{YOLO}} = \lambda_{coord} \sum (x - \hat{x})^2 + (y - \hat{y})^2 + (w - \hat{w})^2 + (h - \hat{h})^2 + \sum (\text{conf} - \hat{\text{conf}})^2 + \sum (\text{class} - \hat{\text{class}})^2*LYOLO =λcoord ∑(x−x^)2+(y−y^)2+(w−w^)2+(h−h^)2+∑(conf−conf^)2+∑(class−class^)2

Where:

- Localization loss penalizes errors in bounding box predictions.
- Confidence loss penalizes incorrect object presence probabilities.
- Classification loss penalizes incorrect class predictions.



3. METHODOLOGY

3.1 Dataset Information

The dataset utilized for this study is the BraTS 2020 (Brain Tumor Segmentation Challenge) dataset, a widely accepted benchmark in the domain of brain tumor segmentation and detection. The dataset comprises 57,195 slices derived from multimodal MRI scans and was originally provided in .nii.gz format. For ease of integration and processing, these volumes were preprocessed and stored in .h5 format, later converted into .jpg format for deep learning model compatibility. An accompanying metadata.csv file was also used, providing metadata about slice numbers, labels, volume information, and background ratios.

BraTS 2020 includes four MRI modalities:

- T1-weighted
- T1Gd (contrast-enhanced T1)
- T2-weighted
- FLAIR

These modalities provide different clinical views of the brain, essential for accurate tumor detection.

3.2 Data Description

For model training, two parallel pipelines were developed—one for YOLOv10 (object detection) and the other for ResUNet (segmentation). The structure of the dataset varied slightly between the two pipelines.

- YOLOv10 Data Structure:
  - Image Files (.jpg): Converted from .h5 format.
  - Annotation Files (.txt): Each image has a corresponding label file containing the tumor's bounding box coordinates and class label.
- ResUNet Data Structure:
  - Image Files (.jpg): Used as input for pixel-wise segmentation.
  - Annotation File (.csv): A CSV file mapping each image path with bounding box coordinates (x_min, y_min, x_max, y_max) and class label for supervised learning.

This structure ensured seamless integration with the respective architectures and allowed the models to learn from spatial and contextual tumor information.

3.3 Data Preparation

Data preprocessing played a crucial role in transforming the raw medical data into a suitable format for training deep learning models. The following steps were applied:

1. Conversion: The .h5 files containing 3D volumetric MRI data were converted into 2D .jpg slices, with a focus on the FLAIR channel for optimal tumor visibility.
2. Resizing: All images were resized to a uniform dimension of 256×256 pixels to standardize input shape across both models.
3. Annotation Generation:
   a. For YOLOv10: .txt files were generated with normalized bounding box coordinates.
   b. For ResUNet: A centralized annotation.csv was created with bounding box info for training the segmentation model.
4. Data Cleaning: Empty or corrupted slices (e.g., with no tumor presence) were filtered out using metadata indicators.
5. Normalization: Intensity values were scaled between 0 and 1 to assist faster convergence during model training.

3.4 Exploratory Data Analysis (EDA)

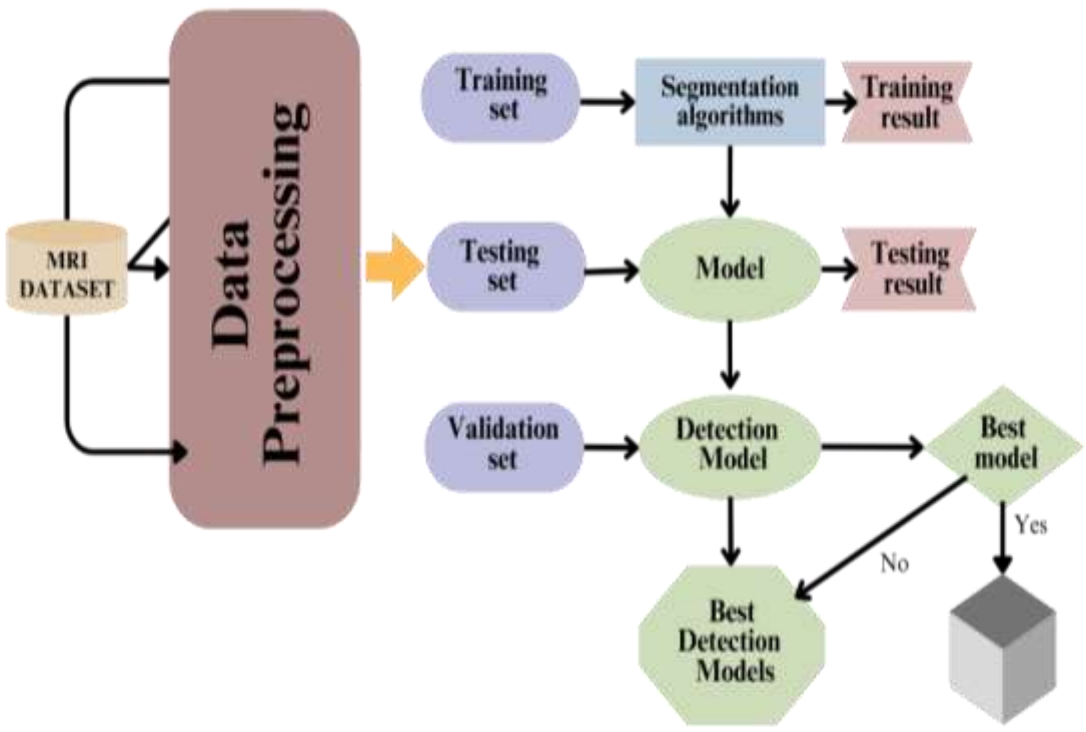
The EDA focused on visualizing the nature and consistency of the data before model training:

- RGB Channel Visualization: The converted .jpg images were examined for quality, modality contrast, and distribution of tumor presence.
- Slice Selection: Central slices from each volume were chosen for their higher likelihood of containing tumor features.
- Intensity Distribution: Visual checks were performed to verify the normalization and contrast across slices.
- Sample Inspection: Random samples were reviewed to ensure annotation accuracy and balance between tumor and non-tumor images.

Although basic, this EDA helped to confirm the validity and readiness of the dataset for training YOLOv10 and ResUNet models.

3.5. System Architecture

The architecture of the brain tumor detection system has been meticulously designed to YOLOv10 for real-time tumor detection.This model approach ensures flexibility, and speed, which are critical requirements in real-world medical scenarios.



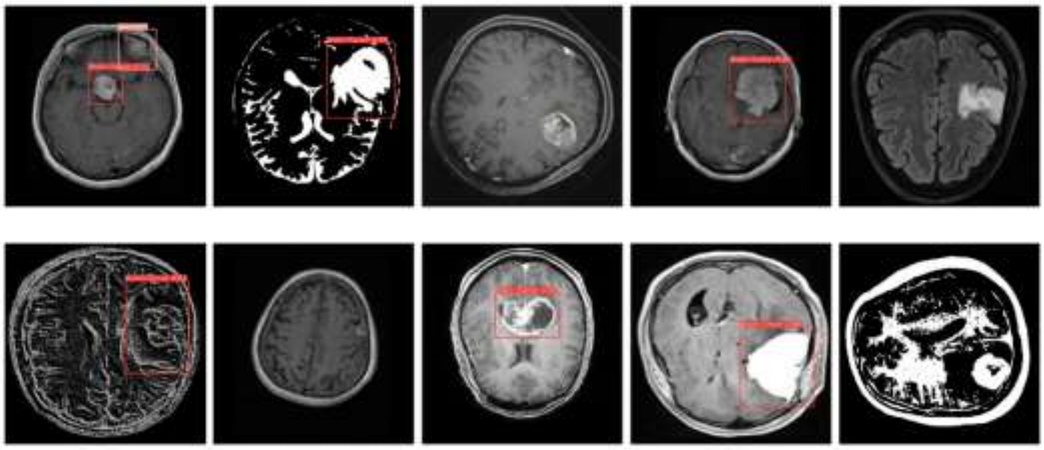
3.5.1. YOLOv10 Pipeline – Real-Time Object Detection

The YOLOv10 (You Only Look Once version 10) pipeline is crafted for real-time detection of brain tumors using bounding boxes. It is particularly suited for time-sensitive environments such as live diagnostics or intraoperative assistance, where decisions need to be made quickly and with a high degree of confidence.

Detailed Steps:

- Input: A 2D MRI slice (in .jpg format), typically extracted from the FLAIR modality of the BraTS dataset, is fed into the pipeline.
- Preprocessing:
    - The image is resized to a standardized dimension, ensuring compatibility with the YOLO input layer.
    - Pixel values are normalized between 0 and 1 to stabilize the training and inference process.
- Model Inference:
    - The preprocessed image is passed through the YOLOv10 model.
    - YOLOv10 applies a series of convolutional layers to extract spatial features and detect the presence of a tumor.
    - It predicts bounding boxes (x_min, y_min, x_max, y_max), class labels, and associated confidence scores.
- Output:
    - The result is a 2D MRI image overlaid with bounding boxes around suspected tumor regions.
    - Each box includes a class label (e.g., tumor) and a confidence score, allowing physicians to gauge prediction certainty.

This pipeline is highly optimized for speed and is ideal for real-time deployments, including live feeds from diagnostic tools or surgical devices.



3.6 Model Evaluation

To assess the performance of our brain tumor detection models, we used appropriate metrics for both object detection (YOLOv10) and semantic segmentation (ResUNet).

YOLOv10 – Object Detection Metrics

- **Mean Average Precision (mAP):**
  Measures detection accuracy across different thresholds. It is calculated by averaging the area under the precision-recall curve for all classes.
  mAP=n1 i=1∑n APi

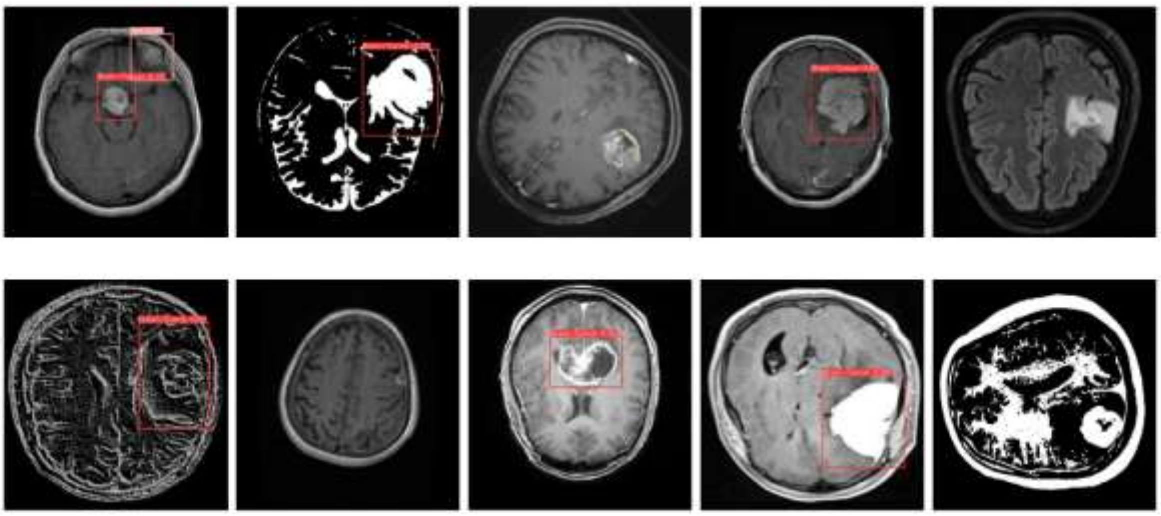
where APi is the average precision for class i, and n is the total number of classes.

- **Frames Per Second (FPS):**
  Measures how many images the model can process per second. Higher FPS implies faster inference, suitable for real-time systems.

3.7 Results and Discussion

YOLOv10 Findings:

- Achieved high **inference speed** and **real-time performance**.
- Showed competent **bounding box accuracy** for tumors of varying sizes and shapes.
- Suitable for integration in real-time surgical support systems or operating theater dashboards.



Visual Output:

- For YOLOv10: Bounding boxes with class labels and confidence scores were overlaid on test images.
- For ResUNet: Color-coded segmentation masks were generated to visualize tumor spread.

Overall, the two models complemented each other—YOLOv10 for fast detection, and ResUNet for fine-grained tumor segmentation—marking a robust framework for future hybrid development.

5. GRAPHICAL USER INTERFACE (GUI)

In order to make our deep learning models accessible and user-friendly, we developed a **Graphical User Interface (GUI)** using the Python-based Gradio library. The GUI serves as a bridge between the complex machine learning backend and end-users such as medical practitioners, researchers, or general users with minimal technical knowledge.

5.1 Purpose of the GUI

The primary objective of the GUI is to allow users to interact with our trained models in a simplified and intuitive manner. Instead of running scripts or using command-line tools, users can now perform tumor segmentation and detection tasks by simply uploading a brain MRI image through the interface. This provides a seamless experience and makes the solution more practical for real-world usage, especially in healthcare environments.

5.2 Technology Used: Gradio

Gradio is a powerful open-source Python library designed to create customizable interfaces for machine learning models. It offers a wide range of input/output components, such as image uploaders, text fields, sliders, and more. Importantly, it enables developers to deploy models as interactive web applications quickly, without requiring any knowledge of web development or front-end design.

Key reasons for selecting Gradio include:

- Easy integration with Python-based models.
- Real-time input/output processing.
- Deployment-ready with automatic link generation for sharing.
- Cross-platform accessibility (desktop, tablet, mobile).

5.3 User Workflow

The GUI developed for this project provides the following functionalities:

- Image Upload: Users can upload a brain MRI scan in image format (e.g., JPG or PNG).

- Segmentation Output: Once uploaded, the ResUNet model processes the image and highlights the tumor region through pixel-wise segmentation.
- Detection Output: Simultaneously, the YOLO model identifies the location of the tumor using bounding boxes.
- Visualization: Both the segmentation map and the detection output are displayed to the user side-by-side for easy comparison and analysis.

This visual feedback allows users to better understand the model's prediction and potentially verify it against manual interpretation or other tools.

5.4 Impact and Usefulness

By implementing a GUI, we ensure that our models are:

- More Accessible: Eliminating the need for coding or technical expertise.
- More Interpretable: Providing visual outputs that make model results understandable.
- More Deployable: The web-based format allows sharing and demonstration with ease, supporting integration into clinical workflows or academic demonstrations.

In the context of medical AI solutions, an interactive and easy-to-use GUI adds immense value by ensuring that sophisticated models can be accessed by healthcare professionals who may not have programming skills but require accurate and immediate insights from medical magingdata.

6. ARCHITECTURAL REQUIREMENT

6.1.Software Requirement

Programming Language: Python

Data Visualization: Matplotlib, Seaborn

Data Analysis and Machine Learning Libraries: Pandas, NumPy, Scikit-learn, TensorFlow/PyTorch

GUI: Gradio

.Hardware Requirement

Computing Infrastructure: High-performance workstation/server for model training and testing the data & also process the image

Data Acquisition Systems: Depending on the type of equipment being used for detection.

7. FUTURE SCOPE

This project presents asingle model strategy using YOLOv10 for brain tumor detection segmentation on MRI scans. While the model is currently deployed independently to explore their specific strengths—YOLOv10 for real-time detection. In future we can integrate it with segementation model like ResUNet for high-precision segmentation—the system's modular architecture unlocks significant opportunities for expansion, deployment, and real-world integration in the future.

1. Hybrid Model Development

The current independent implementation of YOLOv10 and ResUNet allows for targeted optimization, but future work can focus on creating a hybrid pipeline. YOLOv10 could first perform rapid tumor localization, followed by ResUNet's fine segmentation in those specific regions. This not only reduces computational load but also increases accuracy and efficiency, especially valuable in time-sensitive clinical environments.

2. Real-Time Surgical Assistance with Video Support

YOLOv10's architecture supports real-time detection on continuous input, making it ideal for integration with intraoperative video feeds. In future versions, the system could:

- Ingest live surgical video or real-time MRI/CT feed
- Provide continuous tumor boundary tracking during surgery
- Enable real-time visual overlays to assist neurosurgeons

Such an AI-enhanced surgical assistant could drastically improve intraoperative precision, reduce resection errors, and minimize operative time.

3. 3D MRI and Volumetric Tumor Analysis

Future research should move from 2D to 3D MRI volume analysis using advanced architectures like:

- 3D ResUNet
- V-Net
- 3D-YOLO variants

This approach allows for:

- Volumetric tumor detection and segmentation
- Improved spatial continuity between slices
- More accurate tumor volume measurement
- Enhanced preoperative planning and 3D visualization tools for radiologists and surgeons

4. Edge Deployment and Model Optimization

To bring this technology to resource-constrained environments or real-time applications, further efforts can focus on:

- Model pruning, quantization, and conversion to TensorFlow Lite

- Deployment on devices like NVIDIA Jetson Nano, Raspberry Pi + Coral TPU, and mobile devices
- Reduced power consumption and latency

This would make the solution viable for rural health centers, mobile clinics, and portable MRI systems, greatly extending the accessibility of brain tumor diagnosis.

5. Hardware Integration

For practical hospital deployment, integration with medical imaging equipment and neurosurgical tools is crucial. Future implementations can include:

- Plug-and-play support for MRI/CT scanners
- Connection to real-time neuro-navigation platforms
- Integration with AR/VR headsets or touch-screen displays in the OR
- Voice or gesture-controlled interaction with detection overlays

Such hardware integration can bring AI-powered intraoperative visualization to neurosurgeons in a minimally disruptive way.

6. GUI-Based Interactive Interface

To enable real-time usability by medical professionals, the project can include a custom GUI, possibly built with Gradio or Streamlit, offering:

- MRI upload & visualization
- Slice navigation
- Tumor detection overlays
- Tumor segmentation and volume export
- Real-time video feed (for future video-based model support)

This interface can evolve into a **surgeon dashboard** or even a **mobile diagnostic app**.

7. Cloud-Based Deployment & Telemedicine Integration

To support scalability and remote access, the models can be deployed to the cloud (using platforms like AWS, GCP, or Azure), enabling:

- Remote diagnosis by uploading MRI scans via a web interface
- Integration with hospital PACS systems
- Access from multiple endpoints (mobile, browser, medical workstations)

- Telemedicine consultations where rural doctors can consult specialists with AI assistance

This cloud deployment can also support:

- Centralized model updates
- Large-scale data collection for model improvement
- Parallel processing of high volumes of patient data

8. Longitudinal Tracking & Treatment Monitoring

In the future, the system can be extended for tracking tumor progression over time by comparing segmented volumes across multiple patient visits. This will enable:

- Monitoring tumor response to treatment
- Detecting early recurrence or metastasis
- Supporting adaptive therapy planning

CONCLUSION

The detection of brain tumors using MRI imaging remains a critical challenge in the field of medical image analysis, particularly due to the complexity of tumor structures, variations in size and location, and the need for accurate yet fast decision-making. This research project aimed to address these challenges by developing a deep learning-based framework combining YOLOv10 with the goal of achieving high-speed inference in tumor localization and detection.

In the initial phases of the project, we investigated a variety of modern deep learning architectures including YOLOv5, YOLOv7, YOLOv8, YOLOv10, U-Net, and ResUNet. After comparative experimentation and performance evaluation, YOLOv10 was selected as the primary detection model due to its superior real-time performance, reduced computational overhead, and excellent object detection capability even in complex medical images. YOLOv10's one-stage detection pipeline allowed us to quickly identify suspicious regions in MRI slices, making it particularly suitable for time-sensitive clinical applications such as intraoperative navigation and rapid triage.

A significant part of the work involved preprocessing the BraTS2020 dataset, which contains multimodal MRI scans annotated by expert radiologists. This included conversion of volumetric .h5 data into 2D .jpg slices, intensity normalization, and data augmentation to increase the generalizability of the model. A carefully structured pipeline was created for training both models using annotated MRI slices, along with custom loss functions and learning rate scheduling to fine-tune performance.

The combination of YOLOv10 for real-time detection presents a robust framework that bridges the gap between speed and precision, two of the most crucial factors in medical diagnosis and treatment planning. Our system is capable of detecting and outlining tumor regions with minimal latency and high anatomical accuracy, making it potentially valuable for both diagnostic and operative scenarios.

Furthermore, this work lays the foundation for the development of a comprehensive, user-friendly interface, potentially using tools like Gradio or Streamlit, to make the model accessible to medical practitioners with no programming background. Such a tool would allow clinicians to upload an MRI scan and receive real-time feedback on tumor presence, location, and size, along with annotated images, thereby streamlining workflows and reducing diagnostic delays.

In conclusion, this research successfully demonstrates how cutting-edge deep learning models, when carefully integrated and optimized, can significantly enhance the early detection and treatment of brain tumors. While challenges remain—such as generalizing across diverse MRI scanners and patient demographics, and reducing false positives—the proposed system shows great promise as a step toward automated, intelligent, and real-time brain tumor diagnosis. It not only contributes to the growing field of AI in healthcare but also opens up future possibilities for real-world clinical deployment that could improve surgical precision, patient survival rates, and overall healthcare outcomes in neuro-oncology.

REFERENCES

1. Isensee, F., Jäger, P. F., Full, P. M., Vollmuth, P., & Maier-Hein, K. H. (2020). *nnU-Net for Brain Tumor Segmentation*. BraTS 2020 Challenge.

2. Kamnitsas, K., Ferrante, E., Parisot, S., Ledig, C., Nori, A., Criminisi, A., Rueckert, D., & Glocker, B. (2017). *DeepMedic for Brain Tumor Segmentation*. Medical Image Computing and Computer-Assisted Intervention.

3. Havaei, M., Davy, A., Warde-Farley, D., Biard, A., Courville, A., Bengio, Y., Pal, C., Jodoin, P.-M., & Larochelle, H. (2016). *Brain Tumor Segmentation with Deep Neural Networks*.

4. Schwehr, Z., & Achanta, S. (2024). *Brain Tumor Segmentation Based on Deep Learning, Attention Mechanisms, and Energy-Based Uncertainty Prediction*.

5. Guan, X., Yang, G., Ye, J., Yang, W., Xu, X., Jiang, W., & Lai, X. (2022). *3D AGSE-VNet: An Automatic Brain Tumor MRI Data Segmentation Framework*.

6. Wu, W., Li, D., Du, J., Gao, X., Gu, W., Zhao, F., Feng, X., & Yan, H. (2020). *An Intelligent Diagnosis Method of Brain MRI Tumor Segmentation Using Deep Convolutional Neural Network and SVM Algorithm*.

7. Shah, H. A., Saeed, F., Yun, S., Park, J.-H., Paul, A., & Kang, J.-M. (2022). *A Robust Approach for Brain Tumor Detection in Magnetic Resonance Images Using Finetuned EfficientNet*.

8. Nema, S., Dudhane, A., Murala, S., & Naidub, S. (2019). *RescueNet - An Unpaired GAN for Brain Tumor Segmentation*.

9. Khan, A. R., Khan, S., Harouni, M., Abbasi, R., Iqbal, S., & Mehmood, Z. (2021). *Brain Tumor Segmentation Using K-Means Clustering & Deep Learning*.

10. Luu, H. M., & Park, S.-H. (2021). *Extending nn-UNet for Brain Tumor Segmentation*.
11. Bhandari, A., Koppen, J., & Agzarian, M. (2020). *Convolutional Neural Networks for Brain Tumor Segmentation*.
12. Walsh, J., Othmani, A., & Jain, M. (2022). *Using U-Net for Efficient Brain Tumor Segmentation*.
13. Chen, S., Ding, C., & Liu, M. (2018). *Dual-Force Convolutional Neural Networks for Accurate Brain Tumor Segmentation*.
14. Munir, K., Frezza, F., & Rizzi, A. (2022). *Deep Learning Hybrid Techniques for Brain Tumor Segmentation*.
15. Noori, M., Bahri, A., & Mohammadi, K. (2020). *Attention-Guided Version of 2D UNet for Automatic Brain Tumor Segmentation*.
16. Umarani, C. M., Gollagi, S. G., Allagi, S., Sambrekar, K., & Ankali, S. B. (2024). *Advancements in Deep Learning Techniques for Brain Tumor Segmentation: A Survey*.
17. Liu, Z., Tong, L., Chen, L., Jiang, Z., Zhou, F., Zhang, Q., Zhang, X., Jin, Y., & Zhou, H. (2022). *Deep Learning-Based Brain Tumor Segmentation: A Survey*.
18. Mostafa, A. M., Zakariah, M., & Aldakheel, E. A. (2023). *Brain Tumor Segmentation Using Deep Learning on MRI Images*.
19. Karthika, R., & Kannan, A. G. (2023). *Brain Tumor Segmentation with Deep Learning*.
20. Harshini, J., & Gayatri, K. (2021). *Brain Tumor Detection Using Deep Learning Framework*.