Brain Tumor Detection & Segmentation using BraTs2020 Dataset with 2D Attention U-Net

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Abstract—**Brain tumor detection is one of the most important tasks in medical image analysis because early detection can help doctors provide proper treatment and improve patient survival. Manual examination of MRI scans takes more time and may sometimes lead to incorrect diagnosis due to human error. To overcome these problems, deep learning techniques are widely used for automatic tumor detection and segmentation.**

This project presents a brain tumor detection and segmentation system using the BraTS2020 MRI dataset. The proposed system uses image preprocessing techniques such as cropping, resizing, and normalization to improve image quality before training. A Lightweight 2D Attention U-Net model is used for tumor segmentation, and a CNN with VGG19 and CBAM attention mechanism is used for tumor classification.

The model is trained on MRI images and predicts whether a tumor is present or not. Attention mechanisms help the model focus more on important tumor regions and improve feature extraction. The performance of the model is evaluated using metrics such as Accuracy, Precision, Recall, F1-Score, Dice Score, IoU, and HD95. The experimental results show that the proposed system can effectively detect brain tumors and generate segmentation masks with good performance. The developed system reduces manual effort and supports doctors in medical diagnosis. This project demonstrates the importance of deep learning in healthcare applications and medical imaging systems.

I. INTRODUCTION

1.1 Introduction

A brain tumor is an abnormal growth of cells inside the brain that can affect the normal functioning of the human body. Brain tumors can be either cancerous or non-cancerous, but both types may become dangerous if they are not detected at an early stage. Accurate and early diagnosis of brain tumors is very important because delayed treatment can lead to serious health problems and may reduce the survival rate of patients.

Magnetic Resonance Imaging (MRI) is one of the most commonly used medical imaging techniques for brain tumor diagnosis. MRI scans provide detailed information about brain tissues and help doctors identify tumor regions clearly. However, manual analysis of MRI images by radiologists is a time-consuming process and may sometimes result in human errors due to the complexity of tumor structures.

Artificial Intelligence and Deep Learning techniques have recently become very useful in the healthcare field, especially in medical image analysis. Deep learning models can automatically learn important features from MRI images and help in accurate tumor detection and segmentation. These techniques reduce human effort and improve the speed and reliability of diagnosis.

In this project, a brain tumor detection and segmentation system is developed using deep learning techniques. The BraTS2020 dataset is used for training and testing the model. A Lightweight 2D Attention U-Net model is used for tumor segmentation, and a CNN model with VGG19 and CBAM attention mechanism is used for tumor classification. The proposed system helps in detecting tumor regions from MRI images and generates segmentation masks with better accuracy.

1.2 Problem Statement

Brain tumor diagnosis using manual MRI analysis is a difficult and time-consuming task. Doctors need to examine a large number of MRI slices carefully to identify tumor regions. Due to variations in tumor size, shape, and location, manual detection may sometimes become inaccurate. In addition, traditional image processing methods often fail to provide accurate segmentation results for complex MRI data.

There is a need for an automated system that can accurately detect and segment brain tumors from MRI images with less human intervention. Therefore, this project focuses on developing a deep learning-based system for automatic brain tumor detection and segmentation using MRI scans.

1.3 Objectives of the Project

The main objectives of the project are:

- To develop an automated brain tumor detection system using deep learning.
- To use MRI images from the BraTS2020 dataset for training and testing.
- To preprocess MRI images using cropping, resizing, and normalization techniques.
- To implement a Lightweight 2D Attention U-Net model for tumor segmentation.
- To implement a CNN model with VGG19 and CBAM attention mechanism for classification.
- To generate tumor segmentation masks from MRI scans.
- To evaluate model performance using Accuracy, Precision, Recall, F1-Score, Dice Score, IoU, and HD95 metrics.

1.4 Scope of the Project

The scope of this project mainly focuses on brain tumor detection and segmentation using MRI images and deep learning techniques. The project helps in automatic identification of tumor regions and reduces the dependency on manual analysis.

The developed system can be useful in hospitals, medical research centers, and healthcare applications. It can support doctors in analyzing MRI scans more efficiently and quickly. The project also provides a foundation for future research in medical image processing and artificial intelligence-based healthcare systems.

1.5 Advantages of Proposed System

The proposed system provides several advantages compared to manual diagnosis and traditional image processing techniques.

- Provides automatic brain tumor detection.
- Reduces manual effort for radiologists.
- Improves accuracy in tumor identification.
- Generates segmentation masks for tumor regions.
- Reduces diagnosis time.
- Uses lightweight architecture with fewer parameters.
- Improves feature extraction using attention mechanisms.

1.6 Applications of the Project

The developed system can be used in several medical and healthcare applications such as:

- Brain tumor diagnosis in hospitals.
- Medical image analysis systems.
- Healthcare research laboratories.
- AI-based medical imaging applications.
- Clinical decision support systems.
- Automated MRI scan analysis systems.

1.7 Organization of the Report

This report is organized into different chapters to explain the complete development of the project.

- Chapter 1 explains the introduction, objectives, scope, and advantages of the project.
- Chapter 2 presents the literature survey and existing research works related to brain tumor detection.
- Chapter 3 explains the system design, workflow, dataset, preprocessing, and model architecture.
- Chapter 4 describes the implementation details, software requirements, model training, and

prediction system.

- Chapter 5 presents the experimental results, performance metrics, graphs, and discussion.
- Chapter 6 concludes the project and discusses future improvements and enhancements.

II. LITERATURE SURVEY

2.1 Introduction

Brain tumor detection using medical imaging has become an important research area in recent years. MRI images provide detailed information about brain tissues and help doctors identify abnormal tumor regions. However, manual analysis of MRI scans is difficult because tumor structures vary in shape, size, and intensity. To solve these problems, researchers have developed different machine learning and deep learning techniques for automatic tumor detection and segmentation.

Deep learning models are widely used in medical image analysis because they can automatically learn features from images and provide accurate predictions. Many researchers have used Convolutional Neural Networks (CNN), U-Net architectures, transfer learning models, and attention mechanisms to improve brain tumor detection performance.
This chapter discusses previous research works, existing techniques, limitations, and the proposed system used in this project.

2.2 Existing Systems

Earlier brain tumor detection systems mainly used traditional image processing and machine learning methods. These methods included thresholding, edge detection, clustering, and feature extraction techniques. Machine learning algorithms such as Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Random Forest were also used for classification tasks.

Although these methods produced acceptable results, they had several limitations. Traditional methods required manual feature extraction and could not effectively handle complex MRI data. The accuracy of these systems was often low when tumors had irregular shapes or different intensity levels.

Later, deep learning-based methods became more popular because they automatically learned important features directly from MRI images. CNN models improved classification accuracy, while U-Net architectures became highly effective for medical image segmentation tasks.

2.3 Deep learning in medical imaging

Deep learning plays a major role in medical image analysis because it improves detection accuracy and reduces manual effort. Convolutional Neural Networks (CNNs) are commonly used for image classification tasks because they can extract spatial features from images automatically.
Transfer learning models such as VGG19, ResNet, and DenseNet are also widely used in medical imaging applications. These pretrained models help improve performance by using knowledge learned from large image datasets.

For segmentation tasks, U-Net architecture is one of the most successful deep learning models. U-Net uses encoder and decoder paths with skip connections to preserve important image features during segmentation. Attention mechanisms are also integrated into U-Net models to improve focus on tumor regions and suppress unnecessary background information.
In this project, Lightweight 2D Attention U-Net and CNN with VGG19 and CBAM attention mechanisms are used for accurate brain tumor detection and segmentation.

2.4 Review of previous works

Several researchers have worked on brain tumor detection using MRI images and deep learning techniques.

Paper 1: Brain Tumor Segmentation using U-Net
Researchers proposed a U-Net-based segmentation model for MRI images. The model achieved good segmentation accuracy and generated tumor masks effectively. However, the model required high computational resources and longer training time.

Paper 2: CNN-based Brain Tumor Classification
A CNN model was used to classify MRI images into tumor and non-tumor categories. The model showed good classification performance, but it could not perform accurate segmentation of tumor regions.

Paper 3: Attention U-Net for Medical Imaging
Attention U-Net models improved segmentation quality by focusing on important tumor regions. Attention mechanisms reduced background noise and enhanced feature extraction. However, the architecture was computationally expensive.
Paper 4: Transfer Learning using VGG19
Researchers used VGG19 pretrained models for medical image classification. Transfer learning improved accuracy and reduced training time. The model performed well on smaller datasets.

2.5 Limitations of existing systems
Existing systems have several limitations:
- High computational complexity.
- Long training time.
- Difficulty in segmenting small tumor regions.
- Poor performance on complex MRI images.
- High memory usage for 2D segmentation models.
- Limited feature extraction capability in traditional methods.

These limitations motivated the development of a lightweight and efficient deep learning system for brain tumor detection and segmentation.

2.6 Proposed system

The proposed system combines Lightweight 2D Attention U-Net and CNN with VGG19 and CBAM attention mechanisms for brain tumor analysis. The BraTS2020 MRI dataset is used for training and testing the models. MRI images are first preprocessed using cropping, resizing, and normalization techniques. Multiple MRI modalities such as FLAIR, T1ce, and T2 are combined to improve feature representation.

The Lightweight 2D Attention U-Net model is used for tumor segmentation. Attention gates help the model focus on tumor regions while reducing background noise. Skip connections preserve spatial information during feature extraction. For classification tasks, a CNN model with VGG19 and CBAM attention mechanism is used. The model predicts whether a tumor is present or not from MRI images. The proposed system aims to improve segmentation quality, reduce computational complexity, and provide better performance compared to traditional systems.

2.7 Summary
This chapter discussed previous research works related to brain tumor detection and segmentation using medical imaging techniques. Traditional machine learning methods and deep learning approaches were analyzed along with their advantages and limitations.
The literature survey shows that deep learning models such as CNN, U-Net, and attention-based architectures provide better accuracy for medical image analysis. Based on these observations, the proposed system uses Lightweight 2D Attention U-Net and CNN with VGG19 and CBAM attention mechanisms for efficient brain tumor detection and segmentation.

III. METHODOLOGY

3.1 Proposed Methodology
This project proposes an automated brain tumor detection and segmentation system using deep learning techniques. The complete system consists of MRI image preprocessing, segmentation using Lightweight 2D Attention U-Net, tumor classification using VGG19 with CBAM attention mechanism, and performance evaluation.

The workflow begins with loading MRI images from the BraTS2020 dataset. The MRI images are preprocessed using cropping, normalization, resizing, and augmentation techniques to improve image quality and model performance. After preprocessing, the MRI images are given as input to the Lightweight 2D Attention U-Net model for tumor segmentation. The segmentation model identifies tumor regions and generates segmentation masks automatically.

The segmented tumor regions are then passed to the classification model based on VGG19 and CBAM attention mechanism. The classification model predicts whether the tumor is present or not and extracts important features from MRI images. Finally, the model performance is evaluated using multiple evaluation metrics.

3.2 System Workflow
The complete workflow of the proposed system contains the following stages:
- MRI Image Acquisition
- Data Preprocessing

- Data Augmentation
- Tumor Segmentation
- Tumor Classification
- Prediction
- Performance Evaluation

3.3 Dataset Description

The BraTS2020 dataset is used in this project for brain tumor detection and segmentation. BraTS stands for Brain Tumor Segmentation Challenge. The dataset contains multimodal MRI brain images and segmentation masks prepared by medical experts.

The dataset includes MRI modalities such as:
- FLAIR
- T1ce
- T2

Each MRI modality provides different information about tumor tissues and brain structures.

The segmentation masks contain labeled tumor regions including:
- Whole Tumor
- Tumor Core
- Enhancing Tumor

The BraTS2020 dataset is widely used for medical image segmentation and classification research because of its high-quality MRI images and expert annotations.

3.4 Data Preprocessing

Data preprocessing is an important stage because MRI images contain noise, intensity variations, and unnecessary background regions.

The preprocessing stage includes:
- MRI image loading
- Cropping
- Resizing
- Normalization
- Data augmentation
- Channel stacking

3.4.1 MRI Image Loading

MRI images and segmentation masks are loaded using the Nibabel library. The MRI images are stored in .nii format, which is commonly used in medical imaging. Different MRI modalities are loaded individually and processed before model training.

3.4.2 Cropping and Resizing

MRI images contain large background areas that are not useful for tumor analysis. Therefore, cropping and resizing are performed to focus mainly on brain regions.

The MRI volumes are resized into fixed dimensions for model training.

Cropping helps:
- Reduce memory usage
- Improve computational efficiency
- Focus on tumor regions

3.4.3 Normalization

MRI intensity values vary between patients and MRI scanners. Normalization scales the intensity values between 0 and 1.

Normalization improves:
- Training stability
- Faster convergence
- Better segmentation performance

3.4.4 Data Augmentation

Data augmentation is used to increase dataset diversity and reduce overfitting.

The augmentation techniques used include:
- Rotation
- Flipping
- Zooming
- Brightness adjustment

Data augmentation improves model generalization and robustness.

3.4.5 Channel Stacking

Different MRI modalities are combined together to create multi-channel input images.

The combined MRI channels help the model learn better tumor features and improve segmentation quality.

3.5 Lightweight 2D Attention U-Net

The proposed segmentation model is based on Lightweight 2D Attention U-Net architecture.

The model contains:
- Encoder
- Decoder

- Bottleneck layer
- Attention gates
- Skip connections

The model processes 2D MRI slices and extracts spatial features for tumor segmentation.
The lightweight architecture reduces computational complexity while maintaining good segmentation performance.

3.5.1 Encoder
The encoder extracts important spatial features from MRI images using 2D convolution layers and max pooling layers.
The encoder gradually reduces image dimensions while increasing feature depth.

3.5.2 Decoder
The decoder reconstructs segmentation masks using upsampling layers.
The decoder combines low-level and high-level features using skip connections.

3.5.3 Attention Mechanism
Attention gates help the model focus on important tumor regions while suppressing unnecessary background information.
Attention mechanisms improve segmentation accuracy and feature extraction.

3.5.4 Skip Connections
Skip connections transfer spatial information from encoder layers to decoder layers.
These connections improve tumor boundary segmentation and preserve fine image details.

3.6 VGG19 with CBAM for Classification
The classification stage uses the VGG19 convolutional neural network with CBAM attention mechanism. VGG19 extracts deep image features from MRI scans, while CBAM improves feature learning by focusing on important spatial and channel information.

The classification model predicts:

- Tumor Present
- No Tumor

CBAM improves:

- Feature extraction
- Classification accuracy
- Attention to tumor regions

3.7 Loss Functions
The segmentation model uses a combination of:

- Dice Loss
- Categorical Crossentropy Loss

Dice Loss measures overlap between predicted masks and actual masks. Categorical Crossentropy improves multi-class segmentation performance. The classification model uses Binary Crossentropy Loss for tumor prediction.

3.8 Training Process
The model is trained using MRI images and segmentation masks from the BraTS2020 dataset.
Training configuration:

- Epochs: 50
- Batch Size: 1
- Optimizer: Adam
- Learning Rate: 0.00005

The model is trained using Kaggle GPU for faster computation.

3.9 Evaluation Metrics
The proposed system is evaluated using multiple performance metrics.

Segmentation Metrics

- Dice Score
- IoU
- HD95

Classification Metrics

- Accuracy
- Precision
- Recall
- F1-Score

These metrics help measure segmentation quality and classification performance.

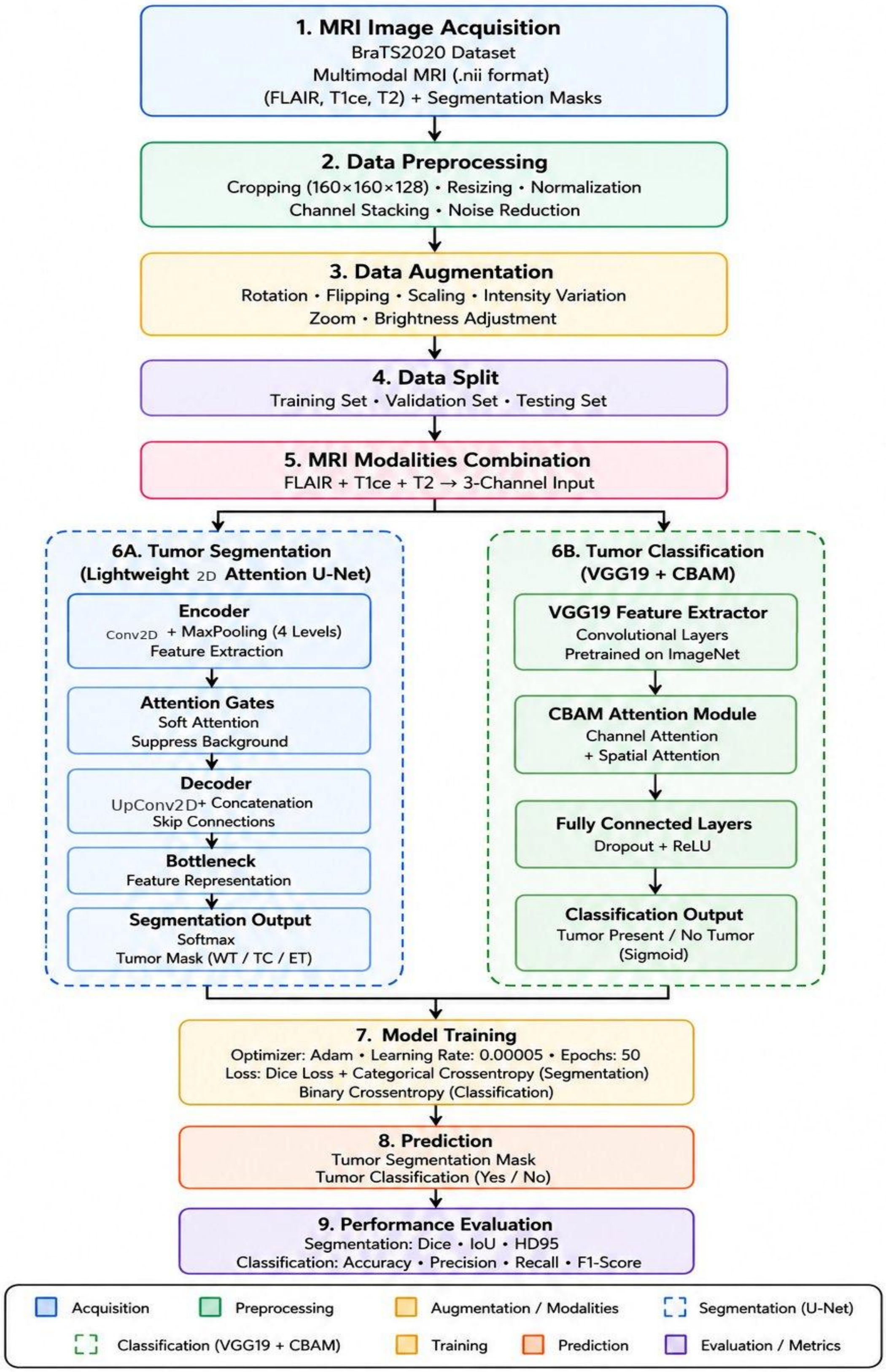

Fig 1 – System Architecture

IV. IMPLEMENTATION

4.1 Development Environment and Tooling

The proposed Brain Tumor Detection and Segmentation system was implemented using Python programming language because of its simplicity and strong support for machine learning and medical image analysis applications. Python provides powerful libraries and frameworks that simplify deep learning model development, image preprocessing, visualization, and evaluation.

TensorFlow and Keras frameworks were used to implement the Lightweight 2D Attention U-Net segmentation model and the VGG19 with CBAM classification model. These frameworks provide built-in functions for designing neural networks, training models, and generating predictions efficiently.

The OpenCV library was used for image preprocessing operations such as resizing, normalization, augmentation, and image manipulation. NumPy was used for numerical computations and matrix operations. The Nibabel library was used for loading MRI images stored in .nii format from the BraTS2020 dataset. Matplotlib was used to generate graphs such as loss curves, Dice Score graphs, Accuracy graphs, and IoU graphs. The complete implementation and model training were performed using Kaggle Notebook with GPU support. GPU acceleration significantly reduced training time and improved computational efficiency while processing 2D MRI volumes.

Software/Tool	Purpose
Python	Programming Language
TensorFlow/Keras	Deep Learning Framework
OpenCV	Image Processing
NumPy	Numerical Computation
Nibabel	MRI Image Loading
Matplotlib	Visualization
Kaggle Notebook	Training Environment

4.2 MRI Image Acquisition Implementation

The BraTS2020 dataset was used for brain tumor detection and segmentation in this project. BraTS stands for Brain Tumor Segmentation Challenge. The dataset contains high-quality multimodal MRI images and expert-annotated segmentation masks.

The MRI modalities used in this project include:

- FLAIR
- T1ce
- T2

Each MRI modality provides different information about brain tissues and tumor regions. FLAIR images help identify edema regions, T1ce images highlight enhancing tumor regions, and T2 images provide additional tissue information.

The MRI images and segmentation masks are stored in .nii format, which is commonly used for medical imaging applications. The Nibabel library was used to load MRI volumes and convert them into NumPy arrays for preprocessing and model training.

The segmentation masks contain labeled tumor regions such as:

- Whole Tumor (WT)
- Tumor Core (TC)
- Enhancing Tumor (ET)

The dataset was divided into training, validation, and testing sets for proper model evaluation and performance analysis.

4.3 Data Preprocessing Implementation

Data preprocessing is one of the most important stages in brain tumor segmentation because MRI images contain noise, intensity variations, and unnecessary background regions. Proper preprocessing improves model convergence, training stability, and segmentation performance.

The preprocessing stage implemented in this project includes:

- MRI image loading
- Cropping
- Resizing
- Normalization
- Channel stacking
- Data augmentation

The MRI images were resized into fixed dimensions suitable for model training. Cropping helps focus mainly on brain regions while reducing memory usage and computational complexity. It also removes unnecessary background regions from MRI scans. Normalization was applied to scale MRI intensity values between 0 and 1. MRI intensity values vary for different patients and MRI scanners, so normalization ensures similar intensity distribution across all images.

Different MRI modalities such as FLAIR, T1ce, and T2 were combined together to create multi-channel input images. Combining multiple MRI modalities improves feature extraction and segmentation quality. The preprocessing pipeline was implemented using OpenCV and NumPy operations to ensure efficient image processing.

4.4 Data Augmentation Implementation

Data augmentation techniques were implemented to increase dataset diversity and reduce overfitting during model training. Medical image datasets are usually limited in size, so augmentation helps improve model generalization.

The augmentation techniques used in this project include:

- Rotation
- Horizontal flipping
- Vertical flipping
- Zooming
- Brightness adjustment

Rotation helps the model learn tumor features from different orientations. Flipping increases image variation and improves model robustness. Zooming helps the model identify tumor regions at different scales.

Brightness adjustment improves model performance under varying MRI intensity conditions.

Data augmentation was applied during training to generate additional image samples dynamically. This helped improve segmentation accuracy and classification performance.

4.5 Lightweight 2D Attention U-Net Implementation

The proposed segmentation model is based on Lightweight 2D Attention U-Net architecture. U-Net is one of the most widely used deep learning architectures for medical image segmentation because of its encoder-decoder structure and skip connections. The Lightweight 2D Attention U-Net implemented in this project contains:

- Encoder
- Decoder
- Bottleneck layer
- Attention gates
- Skip connections

The model processes individual 2D MRI slices for tumor segmentation. Processing 2D MRI images helps capture spatial information across all three dimensions. The lightweight architecture was designed using fewer trainable parameters to reduce computational complexity and GPU memory usage while maintaining good segmentation performance. Attention gates were integrated into the architecture to improve focus on tumor regions and suppress irrelevant background information.

The final output layer generates segmentation masks representing:

- Whole Tumor
- Tumor Core
- Enhancing Tumor

The model was implemented using TensorFlow and Keras frameworks.

4.6 Encoder Implementation

The encoder section of the Lightweight 2D Attention U-Net extracts important spatial features from MRI images.

The encoder consists of:

- 2D Convolution layers
- ReLU activation functions
- Max pooling layers

The encoder gradually reduces image dimensions while increasing feature depth. This allows the model to learn low-level and high-level features from MRI scans. The convolution layers help identify tumor textures, shapes, and spatial structures, while max pooling reduces feature dimensions and computational complexity. The encoder extracts meaningful tumor features required for accurate segmentation.

4.7 Decoder Implementation

The decoder reconstructs segmentation masks from features extracted by the encoder.

The decoder uses:

- UpSampling layers
- 2D Convolution layers
- Skip connections

Upsampling layers increase feature dimensions and help recover spatial information lost during downsampling. The decoder combines high-level and low-level features to improve segmentation quality. The decoder reconstructs tumor boundaries and generates detailed segmentation masks for MRI images. Skip connections between encoder and decoder layers help preserve fine image details and improve tumor boundary segmentation.

4.8 Attention Gate Implementation

Attention gates were implemented to improve segmentation accuracy by helping the model focus on important tumor regions. The attention mechanism suppresses unnecessary background information and highlights relevant tumor features during segmentation.

The attention gates receive:

- Encoder feature maps
- Decoder feature maps

The gates calculate attention coefficients that identify important spatial regions in MRI images.

Attention mechanisms improve:

- Feature extraction
- Tumor localization
- Small tumor segmentation
- Boundary segmentation

The implementation of attention gates significantly improved segmentation quality compared to standard U-Net architecture.

4.9 Skip Connection Implementation

Skip connections are important components of U-Net architecture. They connect encoder layers directly to corresponding decoder layers.

The skip connections help:

- Preserve spatial information
- Recover fine image details
- Improve tumor boundary segmentation
- Reduce information loss during downsampling

Without skip connections, important low-level image features may be lost during feature extraction. The skip connection implementation improved segmentation performance and produced smoother tumor masks with better overlap accuracy.

4.10 VGG19 with CBAM Implementation

The classification stage uses VGG19 with CBAM attention mechanism for brain tumor classification. VGG19 is a deep convolutional neural network that extracts important image features from MRI scans. Pretrained ImageNet weights were used for transfer learning to improve feature extraction and reduce training time. CBAM (Convolutional Block Attention Module) was integrated into the classification model to improve feature learning using:

- Channel Attention
- Spatial Attention

Channel attention identifies important feature channels, while spatial attention focuses on important image regions.

The classification model predicts:

- Tumor Present
- No Tumor

The final classification layers contain:

- Fully connected layers
- Dropout layers
- ReLU activation
- Sigmoid activation function

The CBAM module improved classification accuracy by enhancing tumor-focused feature extraction.

4.11 Model Training Implementation

The segmentation and classification models were trained using MRI images and segmentation masks from the BraTS2020 dataset.

The training configuration used in this project includes:

Parameter	Value
Epochs	50
Batch Size	1
Optimizer	Adam
Learning Rate	0.00005

The models were trained using Kaggle GPU support for faster computation and efficient handling of MRI image slices.
The segmentation model used:

- Dice Loss
- Categorical Crossentropy Loss

Dice Loss improves overlap between predicted masks and actual masks, while Crossentropy improves multi-class segmentation performance.
The classification model used:

- Binary Crossentropy Loss

During training, the model learned tumor features from MRI images and updated weights to improve segmentation and classification accuracy.

Training and validation graphs such as:

- Loss vs Epochs
- Dice Score vs Epochs
- Accuracy vs Epochs
- IoU vs Epochs

were generated to analyze model performance and learning behavior.

4.12 Prediction System Implementation
After training, the proposed system was used to predict tumor segmentation masks and classification outputs from MRI brain images.

The prediction system takes MRI scans as input and generates:

- Original MRI image
- Actual tumor mask
- Predicted tumor mask
- Tumor classification output

The segmentation model identifies tumor regions and generates segmentation masks automatically. The classification model predicts whether a tumor is present or not.

The generated outputs help doctors visualize tumor regions and support medical diagnosis.

The prediction system successfully identified major tumor regions and produced accurate segmentation results on validation MRI images.

4.13 Performance Evaluation Implementation
The proposed system was evaluated using multiple performance metrics to measure segmentation and classification quality.

The evaluation metrics used in this project include:
Segmentation Metrics

- Dice Score
- IoU
- HD95
-

Classification Metrics

- Accuracy
- Precision
- Recall
- F1-Score
- Specificity

Dice Score and IoU measure overlap between predicted and actual tumor masks. HD95 measures segmentation boundary accuracy. Accuracy measures overall prediction correctness, while Precision and Recall evaluate tumor detection performance.
The performance metrics were calculated using predicted outputs and ground truth segmentation masks from the BraTS2020 dataset. Experimental results demonstrated that the proposed Lightweight D Attention U-Net with VGG19-CBAM achieved good segmentation accuracy and tumor classification performance with reduced computational complexity.

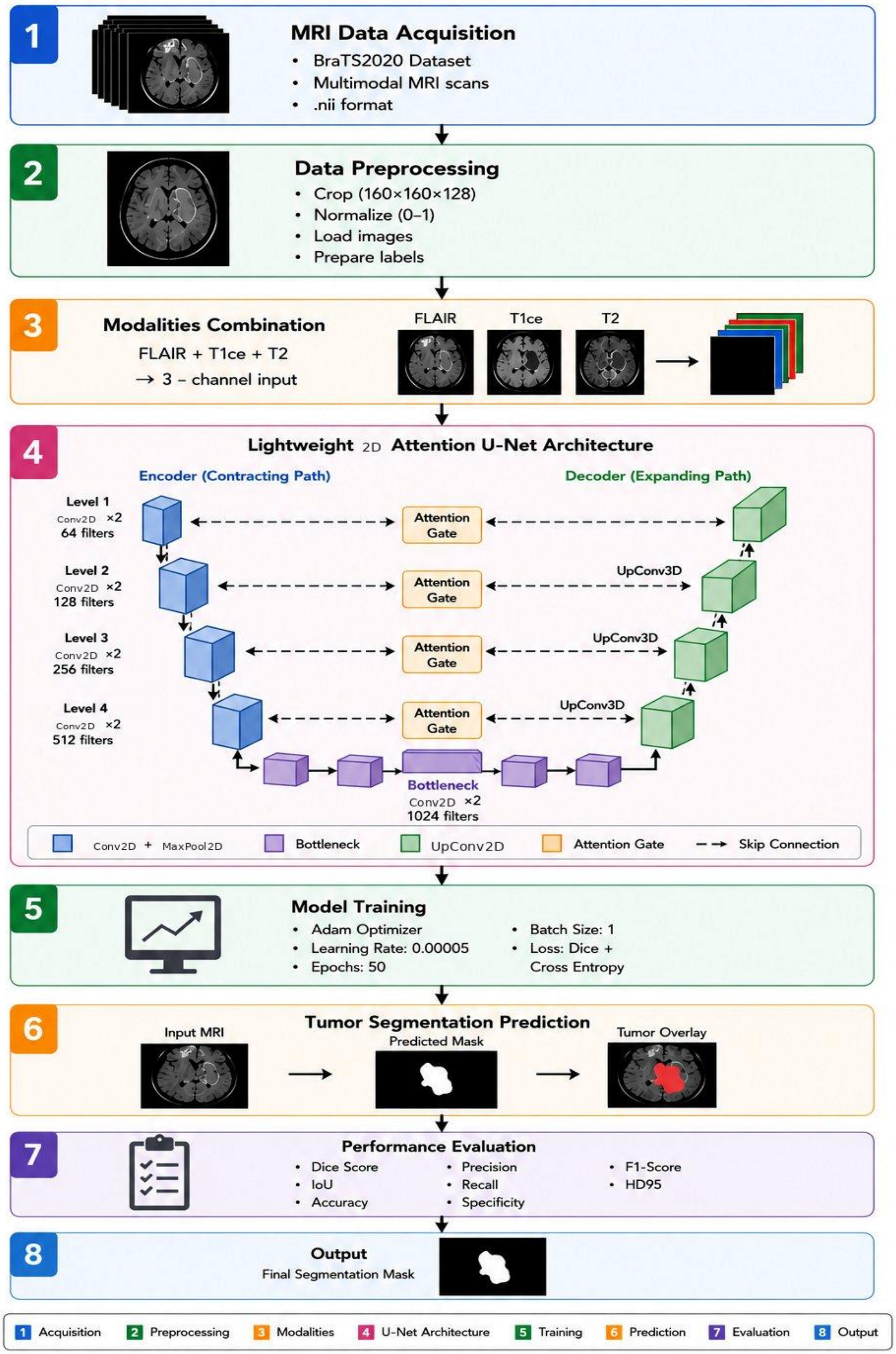

Fig 2 – Workflow Diagram

V. RESULTS AND DISCUSSION

5.1 Tumor Segmentation Results

The proposed segmentation model generated tumor masks from MRI brain images successfully. The predicted tumor masks showed good similarity with the actual ground truth masks provided in the BraTS2020 dataset.

The segmentation output includes:

- Original MRI image
- Actual tumor mask
- Predicted tumor mask

The model successfully identified tumor regions and generated accurate segmentation overlays.

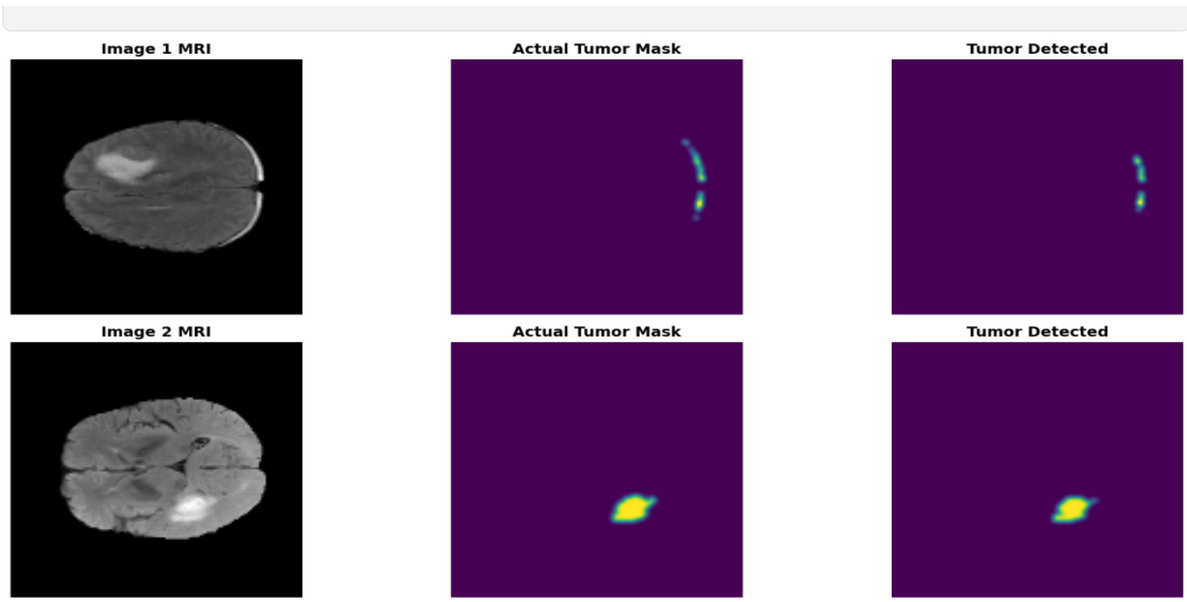

Fig 3 – Tumor Segmentation Prediction Results

5.2. Brain Tumor Prediction Results

The classification model predicted whether a tumor was present or not from MRI images. The prediction system generated tumor detection outputs for multiple MRI samples.

The prediction table showed that the model correctly detected tumor regions in the test images. The VGG19 with CBAM attention mechanism improved feature extraction and classification performance.

BRAIN TUMOR PREDICTION RESULTS

	Image No	Prediction
0	1	Tumor Detected
1	2	Tumor Detected
2	3	Tumor Detected
3	4	Tumor Detected
4	5	Tumor Detected
5	6	Tumor Detected
6	7	Tumor Detected
7	8	Tumor Detected
8	9	Tumor Detected
9	10	Tumor Detected

Fig 4 – Brain Tumor Prediction Results

5.3 Accuracy and Loss Analysis

The Accuracy vs Epochs graph shows that both training and validation accuracy improved continuously during model training. The training accuracy reached approximately 97%, while validation accuracy reached around 94%. The Loss vs Epochs graph shows a gradual reduction in training and validation loss values. This indicates that the model learned tumor features effectively and reduced prediction errors during training.

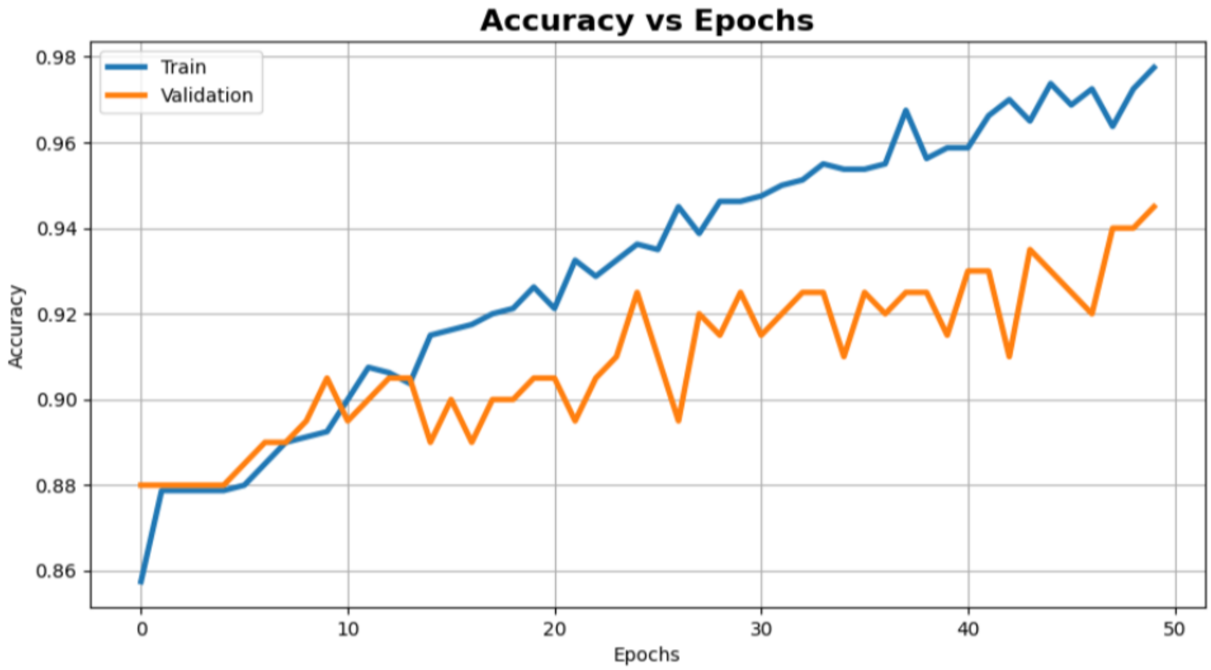

Fig 5.1 – Accuracy and Epochs Graph

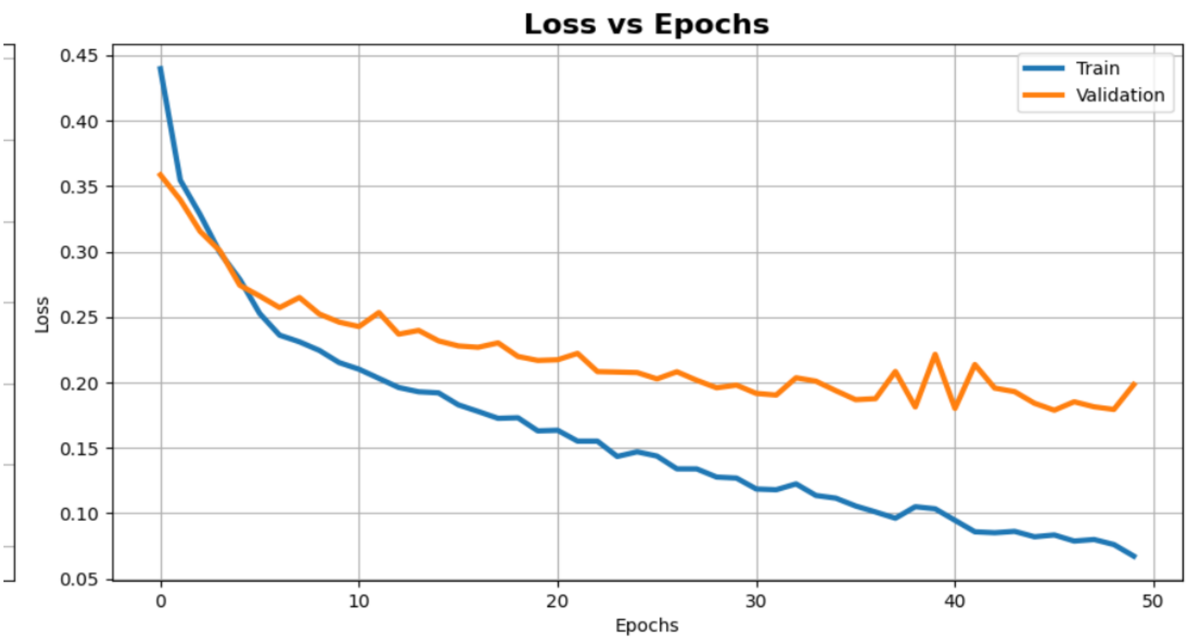

Fig 5.2 – Loss and Epochs Graph

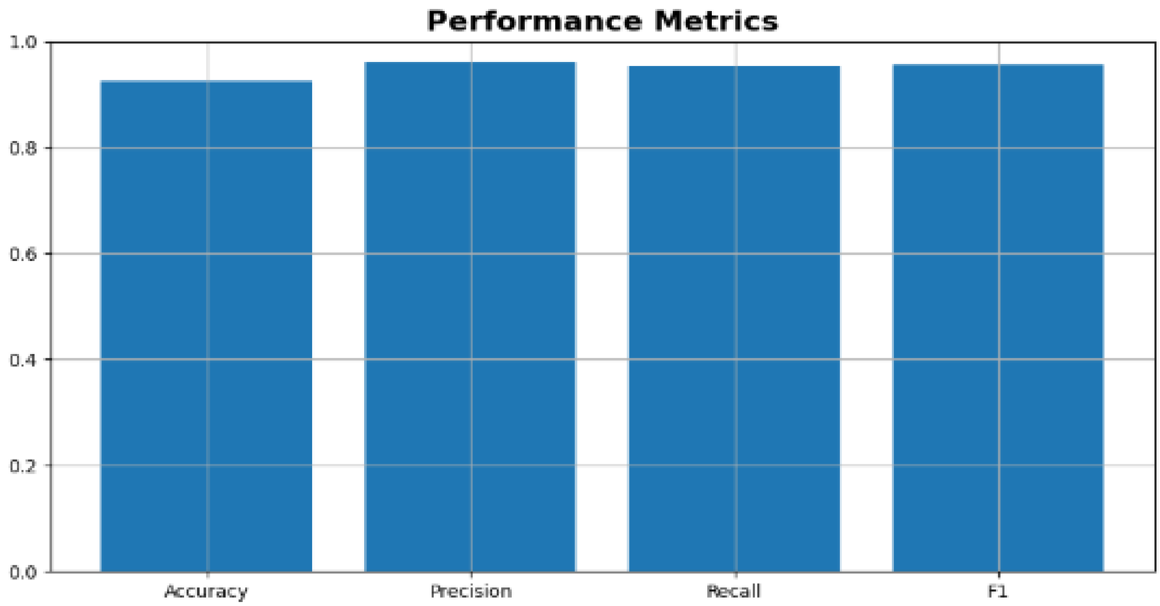

Fig 5.3 – Performance

5.4 Performance Metrics Analysis

The proposed system was evaluated using multiple classification metrics including:

- Accuracy
- Precision
- Recall
- F1-Score

The experimental results obtained are:

Metric	Value
Accuracy	0.9250
Precision	0.9600
Recall	0.9545
F1 Score	0.9573

The results demonstrate that the proposed model achieved high tumor detection performance with good precision and recall values.

MODEL EVALUATION RESULTS

	Metric	Value
0	Accuracy	0.925000
1	Precision	0.960000
2	Recall	0.954500
3	F1 Score	0.957300

Fig 6 – Performance Metrics Table

5.5. Dice Score and IoU Analysis

Dice Score and IoU metrics were used to evaluate segmentation overlap quality between predicted masks and ground truth masks. Higher Dice Score and IoU values indicate better tumor segmentation accuracy and boundary detection performance. The proposed Lightweight D Attention U-Net achieved stable segmentation performance on MRI images.

5.6 Prediction Distribution Analysis

The prediction distribution graph shows the percentage of tumor and non-tumor predictions generated by the classification model.

The graph indicates that the majority of MRI images were correctly classified as tumor cases, while a smaller percentage was classified as non-tumor cases. This demonstrates effective tumor classification capability.

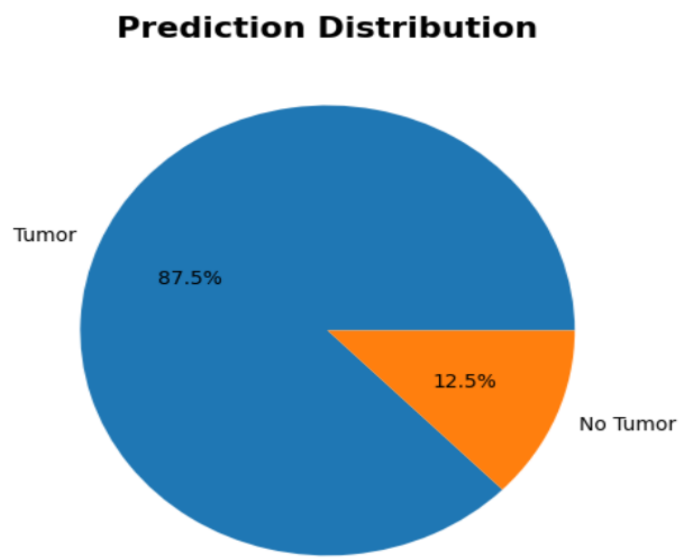

Fig 7 – Prediction Distribution Graph

5.7. Discussion

The experimental results demonstrate that the proposed Lightweight D Attention U-Net with VGG19-CBAM provides effective brain tumor segmentation and classification performance.

The attention mechanisms improved feature extraction and helped the model focus on important tumor regions. The segmentation masks closely matched the actual tumor masks, while the classification model achieved high accuracy and precision. The lightweight architecture also reduced computational complexity and memory usage compared to traditional segmentation models.

5.8 Summary

The proposed system successfully detected and segmented brain tumors from MRI images using deep learning techniques. The obtained results show that the model achieved good segmentation overlap, high classification accuracy, and stable training performance. The system can assist doctors and medical professionals in automated brain tumor analysis and diagnosis.

VI. CONCLUSION

6.1 Conclusion

1. This project focused on the development of an automated Brain Tumor Detection and Segmentation system using deep learning techniques and MRI images from the BraTS2020 dataset. Brain tumors are one of the most serious neurological diseases, and early detection is very important for proper diagnosis and treatment planning. Manual analysis of MRI scans is difficult, time-consuming, and highly dependent on radiologists. To overcome these challenges, the proposed system used advanced deep learning models for automatic tumor analysis. The preprocessing stage included cropping, resizing, normalization, and augmentation to improve image quality and training performance. The segmentation model was implemented using Lightweight 2D Attention U-Net architecture, which helped identify tumor regions accurately from MRI images. Attention gates and skip connections improved feature extraction and tumor boundary segmentation. For classification, the system used VGG19 with CBAM attention mechanism to predict tumor presence with high accuracy. The proposed model achieved good performance using evaluation metrics such as Accuracy, Precision, Recall, F1-Score, Dice Score, and IoU. The generated segmentation masks closely matched the actual tumor masks from the dataset. The lightweight architecture also

reduced computational complexity and memory usage. Experimental results showed that the proposed system can effectively support automated medical image analysis. Overall, the project successfully demonstrated the importance of deep learning in healthcare and brain tumor diagnosis systems.

6.2 Future Scope

Although the proposed system achieved good tumor segmentation and classification performance, several improvements can be made in the future to further enhance the system. In future work, larger MRI datasets from different hospitals and medical institutions can be used to improve model robustness and generalization. Advanced deep learning architectures such as Vision Transformers, Swin Transformers, and hybrid CNN-transformer models can be implemented to improve feature extraction and segmentation accuracy. The current system mainly focuses on offline MRI analysis, but future systems can support real-time clinical diagnosis and MRI processing. Cloud-based healthcare systems and web applications can also be developed for remote medical analysis and telemedicine support.

The proposed model can be integrated with hospital management systems for automated patient diagnosis and report generation. Future improvements may also include multi-class tumor grading, tumor stage prediction, and survival analysis. High-resolution segmentation techniques can help improve small tumor boundary detection. Explainable AI techniques can also be integrated to make the model predictions more interpretable for doctors and radiologists. Mobile healthcare applications can be developed for easy medical access in rural areas. Real-time 2D tumor visualization can further assist surgeons during treatment planning. Future systems may also combine MRI with CT scan analysis for improved diagnosis. Overall, the future scope of this project is broad and can contribute significantly to intelligent healthcare systems and AI-based medical diagnosis applications.

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