BRAIN TUMOR DETECTION USING GRAPH NEURAL NETWORK

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This Report Presented in Partial Fulfillment of the Requirements for
The Degree of Masters of Science in Computer Science and Engineering

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APPROVAL

This Project titled "Brain Tumor Detection using Graph Neural Network", submitted by **Farjana Akter, ID No: 242-25-015** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfilment of the requirements for the degree of M.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on.

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DECLARATION

I hereby declare that this research has been done by me under the supervision of Mr. Md. Sadekur Rahman, Assistant Professor, Department of CSE, Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

Brain tumors make up an important global fitness mission and accurate and timely detection. It is a must in treating for better prognosis of a patient impacted. Most of the conventional so detection methods is based on medical image interpretation by radiodignosts. In fact it is always time may effort consuming subjective and prone to human mistakes. Specially in aid-restrained settings.

This work offers a novel approach for brain tumour diagnosis through GNNs. It is based on the relationship between structural information in brain MRI knowledge. The approach is dedicated to full preprocessing of scientific images. This comprises noise discount, depth normalization and cranium stripping. The and then creative graph sketch the actual of tissues thoughts.

The GNN architecture is intended to capture all local characteristics and global structural relationships among the brain scans.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Brain tumors are abnormal masses that develop in the brain. They can be either malignant (cancer-type) or benign (non-cancer type). Because they are very sensitive to their location and could interfere with very important neurological functions. Brain cancer is, regarded to be one of the very intensive conditions to diagnosis and treat. Brain tumors account for around two percent of all cancers worldwide, reports the World Health Organization. Be that as it may, their distribution may differ in various populations and geographical areas.

1.2 Motivation

Motivation The motivation of the study is that there is an urgent need for reliable and efficient brain tumor detection methods that can be widely available. Currently, medical imaging reviewed by radiologists play a major role in the diagnosis of brain tumor. Yet this reliance has left us with a series of enduring problems.

Lack of experts: Neuro-radiologists with specialized training are in short supply around the world. Outstrips the supply, with this shortage being more severe in low-resource and rural areas.

1.3 Rationale of the Study

GNNs can efficiently describe both local characteristics and global relationships. Since they are built to cope with graph-structured data. This feature is especially helpful in the diagnosis of brain cancers since these tumors might have uneven borders and complicated forms that might be better depicted by graph structures.

Additionally, combining GNNs with sophisticated image preprocessing methods can greatly enhance a model's capacity to manage the noise and unpredictability present in medical pictures. By integrating these methods, this study seeks to visualize a trustworthy and accurate brain tumor identification system that can help radiologists with their diagnostic work.

1.4 Research Questions

After going through many scholarly articles the following important questions have been developed in order to direct this investigation:

1. In comparison to conventional CNN techniques, how well can a Graph Neural Network model identify and categorize brain cancers in MRI scans?

2. What preprocessing techniques are most effective for enhancing MRI data prior to graph representation and GNN analysis?

3. In what ways can distinct tumor kinds, sizes and locations affect the performance of GNN-based models?

4. Can the proposed GNN model provide interpretable results that can assist radiologists in understanding the basis of its predictions?

5. Is the proposed model scalable and adaptable for integration into clinical workflows in diverse healthcare settings?

1.5 Expected Output

The project aims to deliver the following outputs:

- A rich dataset of MRI scans for brain, including various tumors (glioma, pituitary, meningioma etc.) and healthy cases, properly annotated and preprocessed.

- A strong MRI data preparation pipeline that includes tissue segmentation, noise reduction, intensity normalization and skull stripping.

- An innovative graph representation method for brain MRI data that effectively captures structural relationships.

- A GNN-based model that outperforms baseline methods in terms of performance measures for the identification and classification of various brain tumor conditions.

1.6 Project Management and Finance

A Gantt chart-based schedule tracks progress, ensuring timely completion of tasks such as concatenated feature testing, attention mechanism integration and deep learning model development.

Item	**Description**	**Cost (USD)**
Computing Resources	Google Colab Pro subscription — $10/month × 4 months	$40
Data Storage & Backup	Cloud storage (Google Drive) — included in existing plan	$0
Software &Libraries	All open-source (Python, Scikit-learn, TensorFlow, PyTorch, BioPython)	$0
Miscellaneous	Internet, documentation printing and presentation	$20

	materials	
Total Estimated Cost	Self funded	$60

Figure 1.6.1: Finance Table

1.7 Report Layout

The report has been divided in 6 sections described below:

Chapter I: Here the problem, incitement, research questions, objectives and the project's overall scope has been described.

Chapter 2: Chapter reviews the background of the proposed study, literature review, defines terminologies, evaluates related works as well as highlights challenges.

Chapter 3: Has the contents that describe a methodology, creation of the dataset, preprocessing dataset, model architecture and implementation tools.

Chapter 4: There is experimental setup, results, evaluation measures and findings analysis.

Chapter 5: Contains the increased implications of the study to the society, ethics, environment and future sustainability.

Chapter 6: In this section summary the study and deduction of the main findings and suggestions are analyzed to conduct in the future.

CHAPTER 2

BACKGROUND

2.1 Preliminaries / Terminologies

Prior to going inside the elaboration of our methodology, it is crucial to clarify the main ideas and terms employed in this study:

Brain tumor: A malignant (cancerous) or benign (non-cancerous) aberrant development of brain cells. Common kinds include gliomas, meningioma, pituitary tumors and metastatic tumors.

MRI or Magnetic Resonance Imaging: Hertzian emission and rugged magnetic fields are utilized in magnetic resonance imaging. It is a noninvasive medical imaging process that creates really fine detailed images of one's brain and other bodily regions. Graph Neural Networks (GNNs): It is one type of neural networks that are intended to function with graph-structured data, in which nodes stand for entities and edges for their interactions. Node Embedding: the procedure that maintains the structural characteristics of a network by mapping its nodes to a low-dimensional vector space.

Message passing is a basic GNN function in which nodes update their representations by exchanging information with their neighbors. Graph Convolution: An operation that applies the convolution principle to graph-structured data, such as photographs.

In order to concentrate analysis on brain structures, non-brain tissues are removed from MRI scans by a technique known as skull stripping. The act of defining the borders of a tumor in medical pictures is known as tumor segmentation and it is essential for both diagnosis and therapy planning.

A ROI also referred to as region of interest is a particular area in an image that is selected for additional examination, in this example; the areas are probable tumors.

2.2 Related Works

We have prepared a detailed table after studying a good number of papers. In 2.3 the details can be found.

2.3 Relative comparison Analysis and Summary

Here I have generated a table of related studies to summarize the key aspectsof these related works:

Table 2.3.1: Literature Review

Year	Authors/Publisher	Reference	Keywords	Summary	Dataset Used	Algorithm Used	Accuracy (%)
2016	Pereira et al.		CNN, Segmentation	Brain tumor segmentation with small kernels	BraTS	CNN	88.7
2017	Havaei et al.	[2]	Multi-path CNN	Local and global features for segmentation	BraTS	CNN	87.1
2017	Kamnitsas et al.	[3]	3D CNN	Dual pathway architecture for lesion segmentation	BraTS	3D CNN	89.3
2018	Chen et al.	[4]	Cascaded CNN	Improved accuracy for small tumors	BraTS	CNN	90.1
2018	Zhao et al.	[5]	FCN, CRF	Refined segmentation with CRFs	BraTS	FCN+CRF	89.8
2019	Wang et al	[6]	3D U-Net	Residual connections for segmentation	BraTS	3D U-Net	90.5

2019	Myronenko	[7]	VAE	Encoder-decoder with VAE regularization	BraTS	3D CNN	90.4
2019	Zhou et al.	[8]	Attention	Interpretable brain tumor classification	Custom	CNN	92.3
2019	Deepak et al.	[9]	Transfer Learning	GoogleNet for classification	Figshare	GoogleNet	94.2
2019	Sajjad et al.	[10]	Data Augmentation	Multi-grade classification	Custom	CNN	91.8
2020	Litjens et al.	[11]	Survey	Comprehensive review of medical AI	N/A	Survey	-
2020	Anaraki et al.	[12]	3D CNN	Textural features for classification	Custom	3D CNN	93.1
2020	Swati et al	[13]	Fine-tuning	Block wise fine tuning for classification	Figshare	CNN	94.5

2020	Zhang et al.	[14]	GNN	Graph representation of MRI slices	BraTS	GNN	91.2
2021	Wang et al.	[15]	Transformer	Long-range dependencies in segmentation	BraTS	Transformer	91.7
2021	Isensee et al	[16]	nU-Net	Self-configuring segmentation framework	BraTS	nnU-Net	91.9
2021	Jia et al.	[17]	Multi-modal GNN	Integration of different MRI sequences	Custom	GNN	93.4
2021	Zhou et al.	[18]	Graph Convolution	Spatial relationships in segmentation	BraTS	GNN	92.1
2022	Chen et al.	[19]	Attention GNN	Interpretable classification	Custom	GNN	94.7
2022	Liu et al.	[20]	Hybrid CNN-GNN	Local features and	BraTS	CNN+GNN	93.8

				global context			
2022	Wang et al.	[22]	Hierarchical GNN	Multi-scale feature fusion	Custom	GNN	95.1
2022	Zhang et al.	[22]	Self-supervised	Reduced need for annotations	BraTS	GNN	90.8
2023	Kumar et al.	[23]	Multi-scale GNN	Improved small tumor detection	BraTS	GNN	93.9
2023	Li et al.	[24]	GAT	Focus on relevant regions	Custom	GNN	95.3

2.4 Scope of the Problem

Even though deep learning has made great strides in brain tumors diagnosis. Still few problems still need to be resolved:

- Limited Representation of Structural Relationships
  - Most existing approaches, particularly CNN-based methods, treat brain MRI as grid-like structures. Failing to adequately capture the complex anatomical relationships within the brain.
- Handling Heterogeneous Data
  - There are difficulties with generalization. As brain tumors vary greatly in size, occurring location, shape and appearance.
- Interpretability
  - As many DL learning frameworks works as "black boxes”. It is often challenging for professionals in the medical sector to comprehend. Be confident in their descisions.
- Computational Efficiency

- Complex models cannot be practically implemented in clinical settings. Due to the computationally demanding nature of processing 3D MRI data.

- Data Scarcity
    - There aren't enough prime quality annotated medical imaging data available. Specially for very rare tumor variances.

Our research addresses these gaps. By developing a GNN-based approach which can effectively model the structural relationships in brain data. It provides interpretable results and handle the heterogeneity of brain tumors. While maintaining computational efficiency.

2.5 Challenges

There are many challenges to overcome. In the creation of a GNN-based system for brain tumor detection:

- How may we build the graph representation
- How may we complete data preprocessing
- Model Complexity
- Evaluation and Validation
- Integration with clinical workflows

CHATPER 3

RESEACRCH METHOODOLOGY

3.1 Reesearch Subjects and Instrumentations

The primary objectives of this research are as follows:

- To create a useful technique. Display brain MRI data as graphs. Reflecting both global structural correlations and local details.
- To create and put into practice a hybrid GNN architecture that, using graph representations, can precisely identify and categorize brain cancers.
- To compare the effectiveness of our suggested strategy with existing cutting edge approaches and conventional ANN-based methods.
- To create visualization tools that can be used to highlight areas of interest in the MRI scans and assist in interpreting the model's predictions.

Both custom-collected and publically accessible datasets were used in the study and all tests were carried out in a controlled computer environment to guarantee repeatability.

3.2 Dataset Collection Process or Dataset Utilized

Data Collections

The dataset we used in this research is compiled from Kaggle.

Data Labeling

All images were labeled by experienced radiologists according to the following classes:

- **No Tumor:** No detectable tumor or abnormality.
- **Glioma**
- **Meningiomas**
- **Pituitary**

Table 3.2.1: Description of Dataset

Class Name	**Original Images**	**After Augmentation**
No Tumor	1595	3000
Glioma	1321	3000
Meningioma	1339	3000
Pituitary	1457	3000
Total	5712	12000

Directory Structure:

/dataset/

---train/

---validation/

---test/

To comply with deep learning architectures' input requirements, images were scaled uniformly to 224 x 224 pixels.

3.3 Statistical Analysis

Several statistical methods were implemented. Mainly to validate the standardness of the dataset and evaluate the designed models performance:

- Descriptive Statistics
- Class Balance Assessment
- Performance Metrics:
    - Accuracy
    - Precisions
    - Percentage of true positive instances that was detected precisely is defined, recall or sensitivity.
    - F1-Score: It defines harmonic mean of recall and precision.
    - The capacity of the model to transform between classes is shown by the Area under the roc-curve (AUC-ROC).
- Statistical Tests:
    - ❖ McNemar's Test : To collate the output of different models.
    - ❖ Cohen's Kappa: To appraise agreement of inter-rater between the model and human experts.
    - ❖ Confidence Intervals: To determine the results statistical significance.

All statistical analyses were performed using Python libraries such as SciPy, StatsModels and Scikit-learn.

3.4 Proposed Methodology/Applied Mechanism

Following image can describe my methodology for this research:

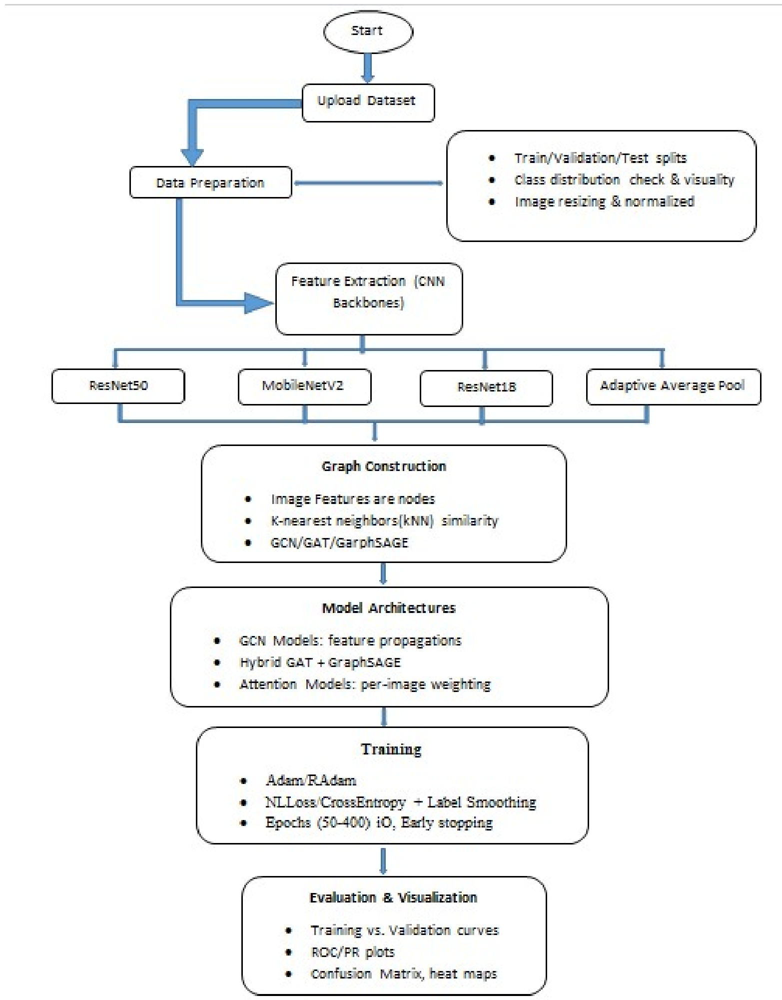

Fig 3.4.1 : Methodology Diagram

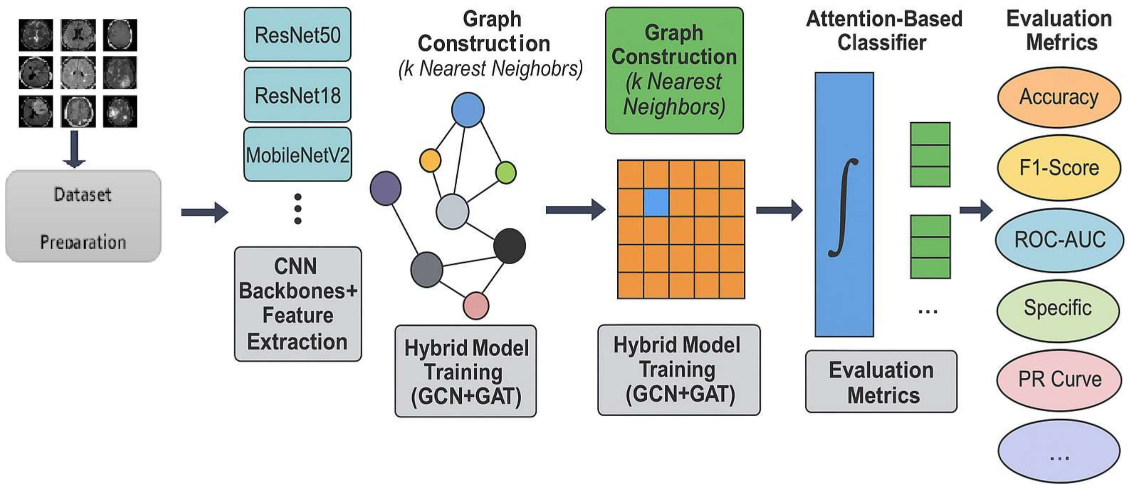

Figure 3.4.2 : Architectural Diagram for Brain Tumor Detection comparing a proposed Hybrid GCN-based framework and Attention-based Framework

Process development pipeline consists of several key stages:

Step 1: Image Preprocessing

Preprocessing can improve the model's interpretability and image quality. Every one of the following methods was applied:

Resizing: Every image was resized to 224x224.

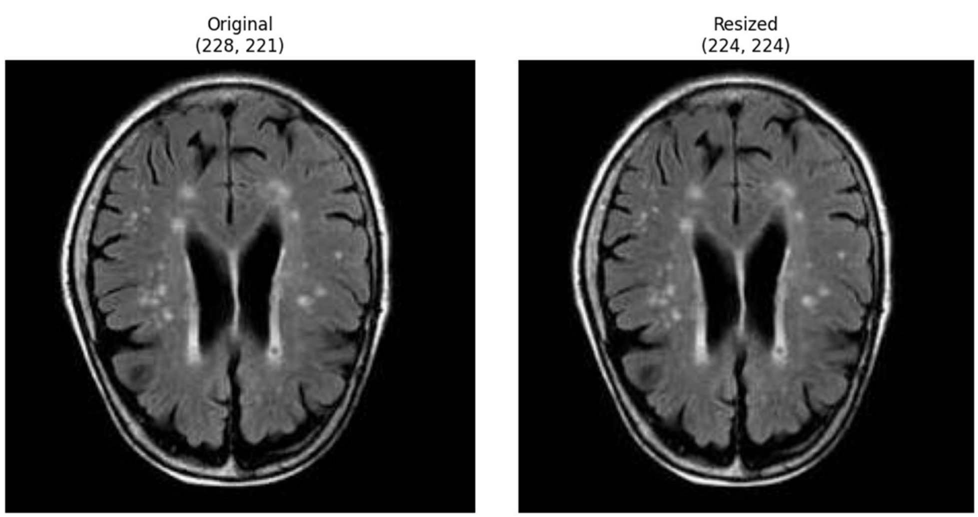

Figure 3.4.3: Resized Image

Every image is subjected to CLAHE in turn to improve contrast and reveal any otherwise undetectable illness patterns that could be hidden by variations in lighting or color.

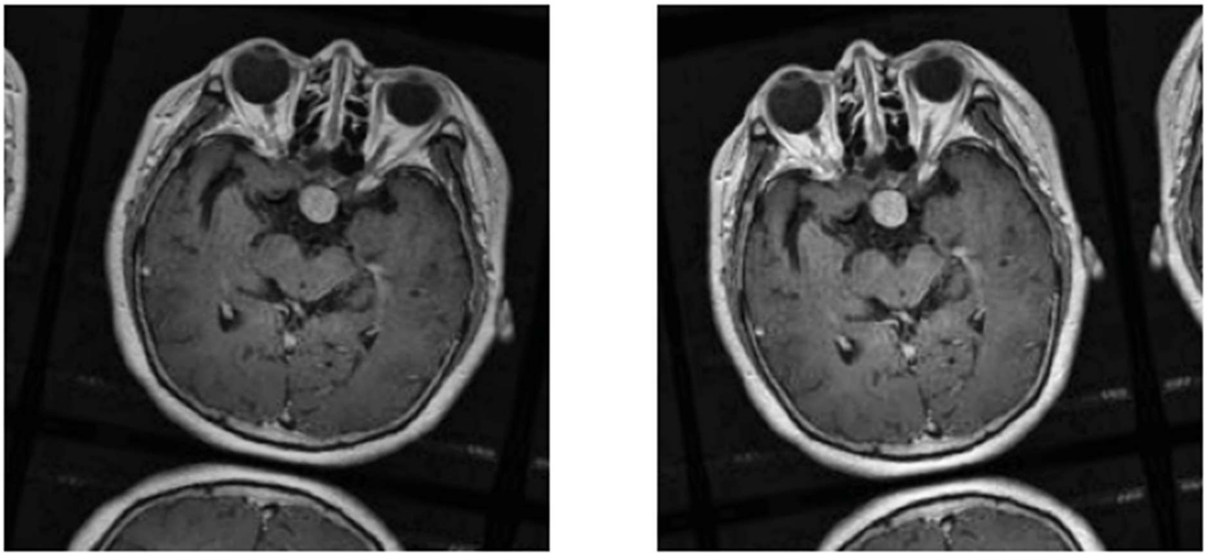

Figure 3.4.4: Contrast Stretched Image

Normalization: After scaling the pixel values to [0,1], using the standard deviation and ImageNet mean values were normalized.

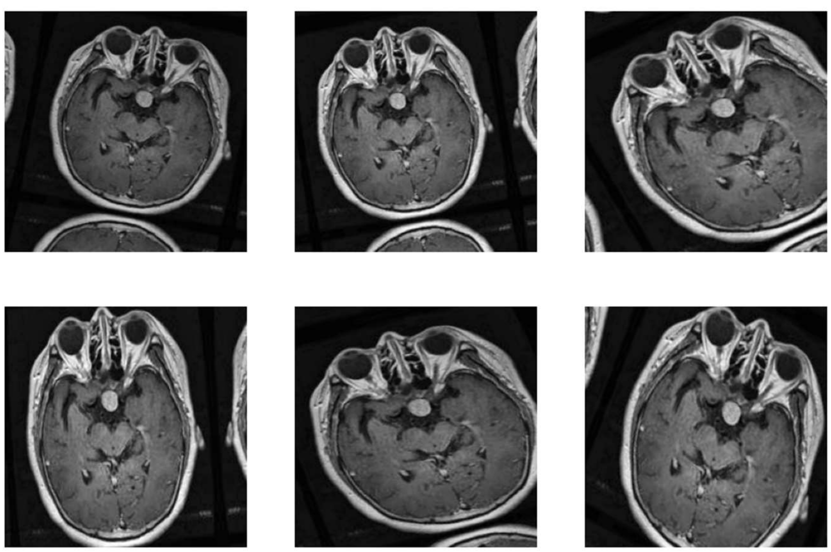

Figure 3.4.5: Augmented Image

Data Augmentation: Task is applied to synthetically grow the size of the dataset and avoid overfitting. Included:

- Rotation (30 degrees /-30 degrees)
- Zoom (maximum of 20%)
- Vertical and horizontal flipping
- Brightness shift
- Width shift/Height shift

Table 3.4.1 : Original Count Vs Augmented Count Table

	Class	Original count	Augmented count
0	notumor	1595	3000
1	pituitary	1457	3000
2	meningioma	1339	3000
3	glioma	1321	3000

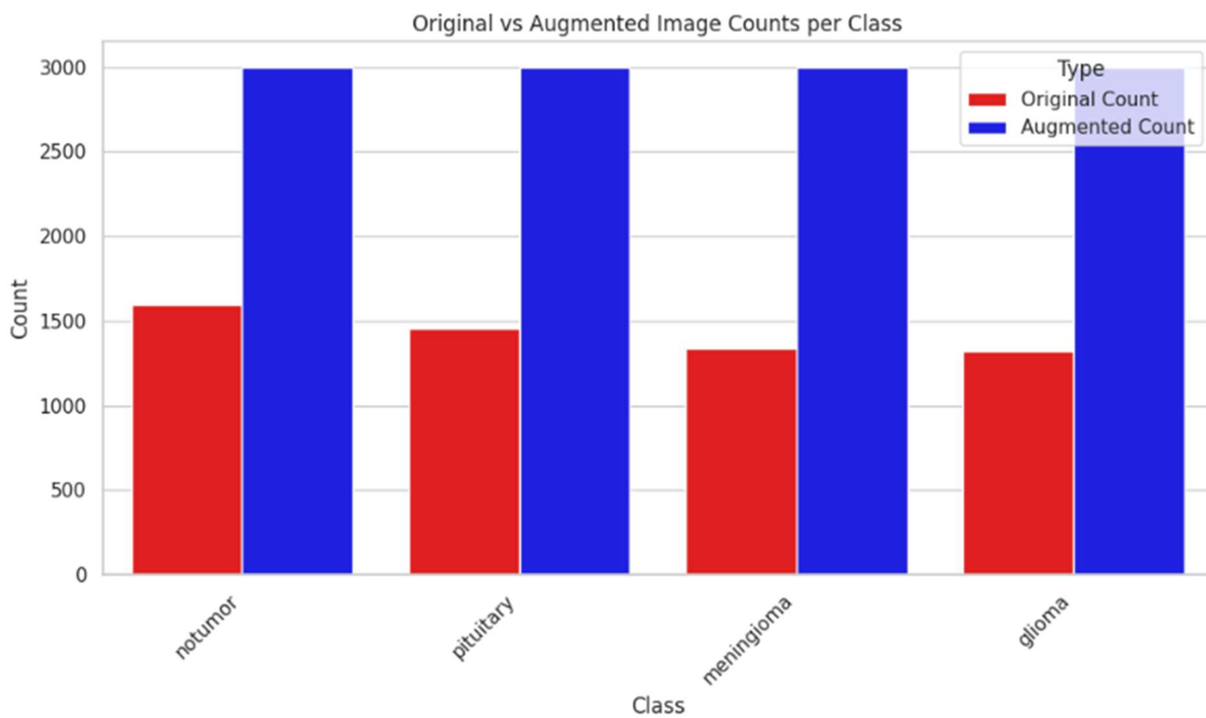

Figure 3.4.6: Visual comparison between original and augmented images

Step 2: Splitting of Dataset

A stratified sampling approach was used to differentiate the dataset into two that is training and test dataset. Then the training dataset was split into train dataset into 80% to train and 20% to validation dataset. Here we also experimented with 75-15-15 split for train-test-validation but the 80-2O ratio generated best results

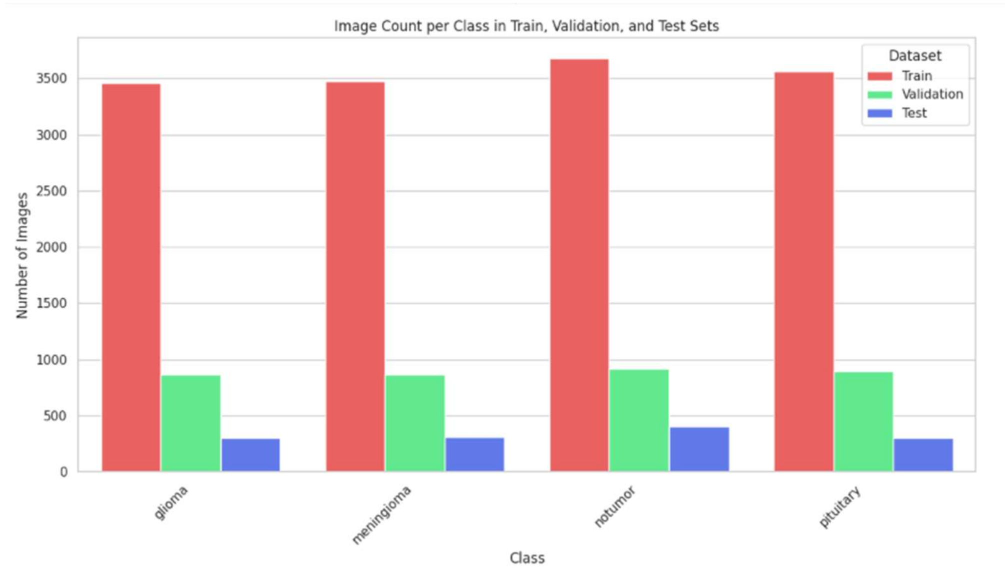

Figure 3.4.7: Visual of image counting per class in train, test and validation set

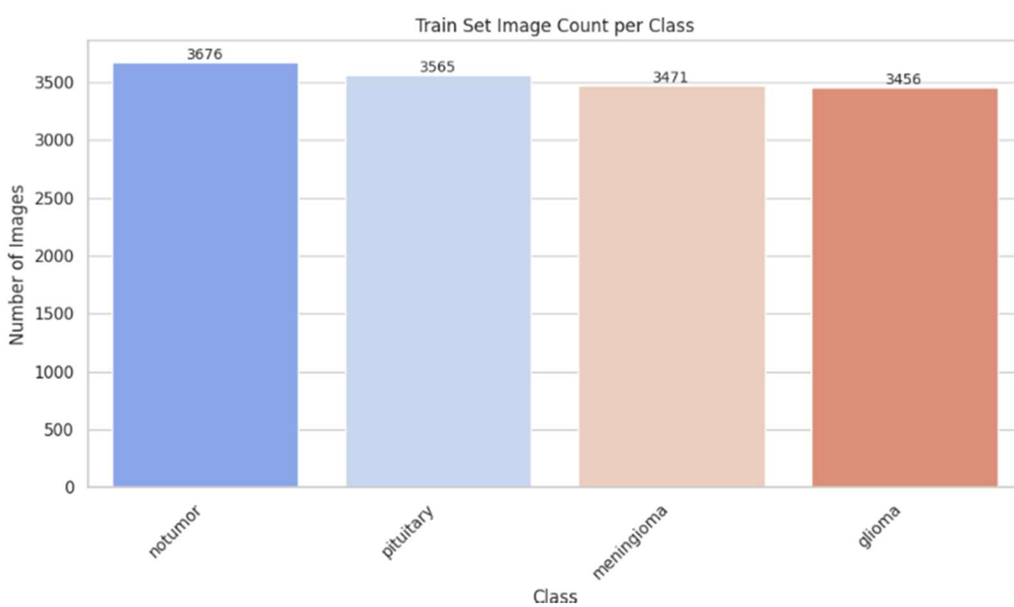

Figure 3.4.8: Visualization of train dataset image count per class

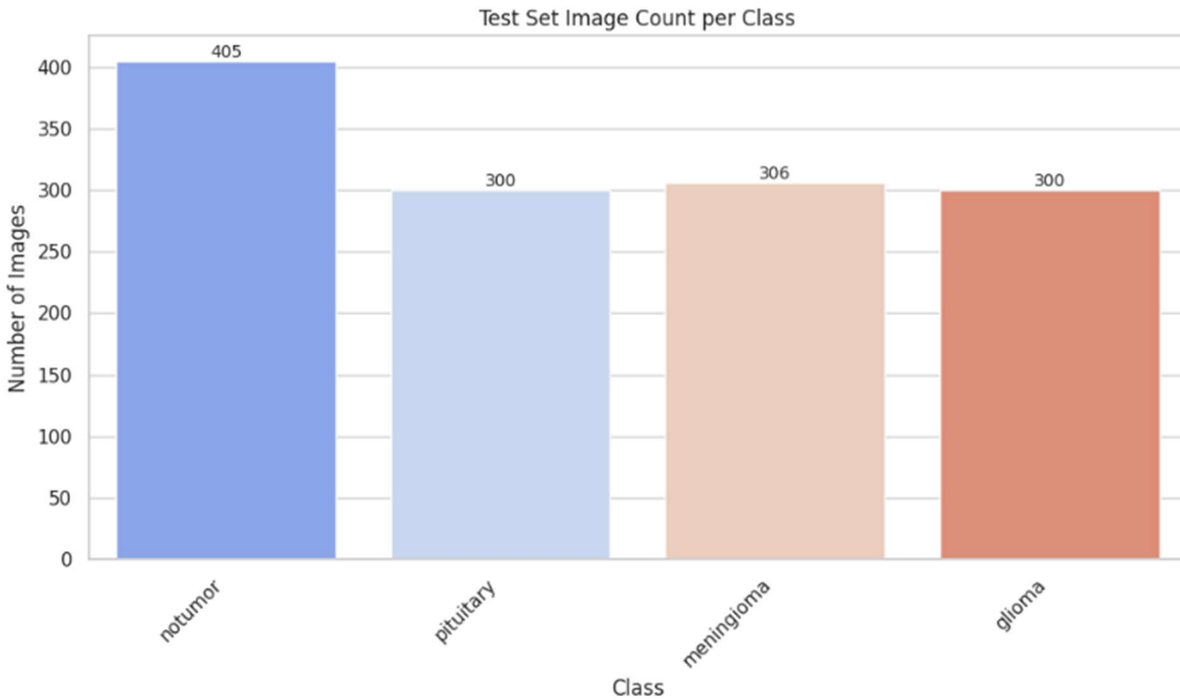

Figure 3.4.9: Visualization of test dataset image count per class

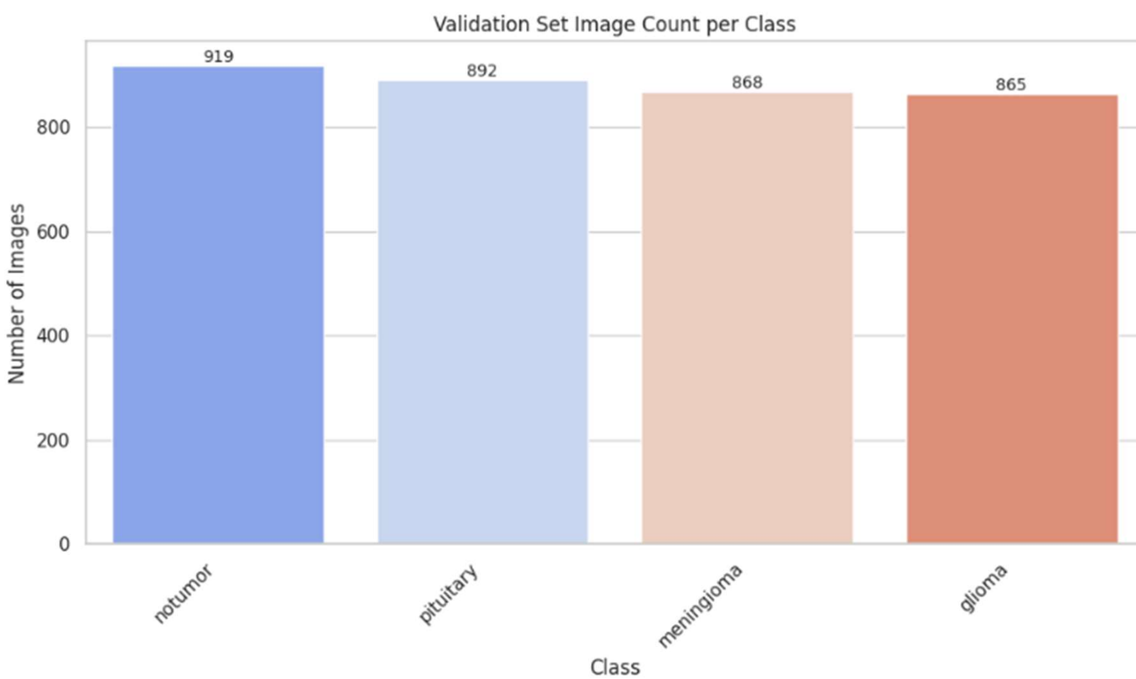

Figure 3.4.10: Visualization of validation dataset image count per class

Step 3: Feature Extraction

We used three different CNN backbones to extract features:

- ResNet50 as it is one of the most widely used deep residual networks.
- MobileNetV2 as it is lightweight and also an efficient CNN.
- ResNet18 as it is a shallower residual network.

Features are extracted from the final convolutional layers before classification head and are pooled using Adaptive Average Pooling.

Step 4: Graph Construction for GNN-based approaches

- After extracting features of images are treated as nodes.
- k-nearest neighbors (kNN) graph is built using feature similarity where the value of k was 5
- Then the generated graph served as input to GCN (Graph Convolutional Network's), GAT (Graph Attention Network's) or GraphSAGE.

Step 5: Model Architectures
Two models were developed and compared:

Model A: Hybrid GCN-based models: We used GCNConv layers to propagate feature information through the graph then combined GAT and GraphSAGE with dropout regularization.

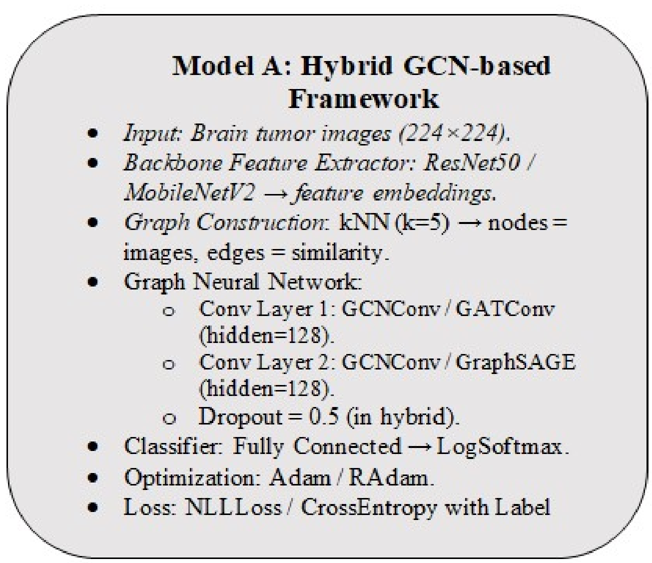

Figure 3.4.11: Proposed Hybrid GCN-based Framework

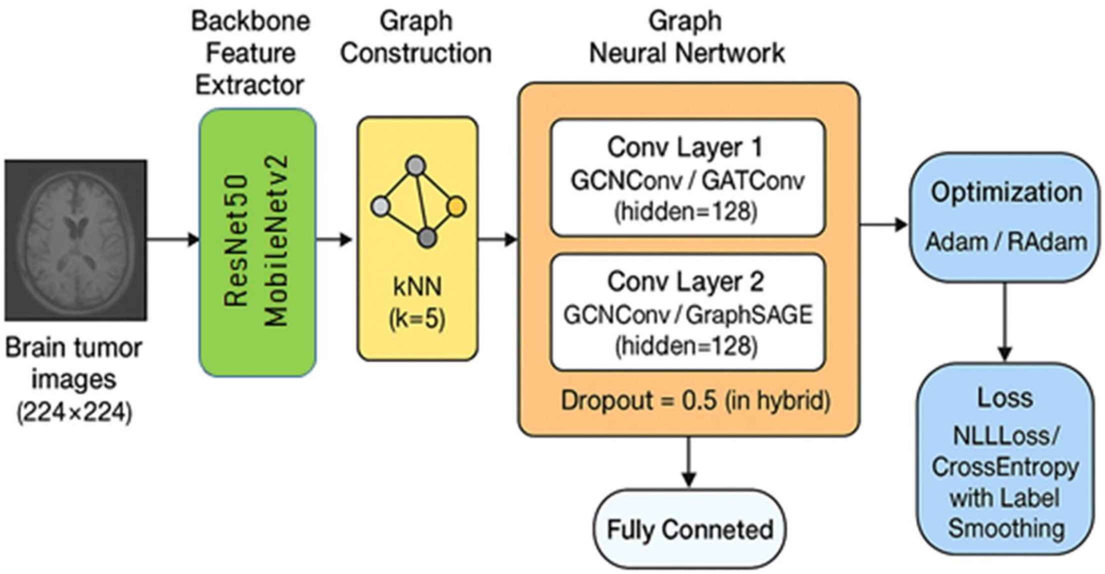

Figure 3.4.12: Architectural diagram for proposed hybrid GCN-based Framework

Model B: Attention-based models: In this model per-image attention weight is learned for feature refinement before classification.

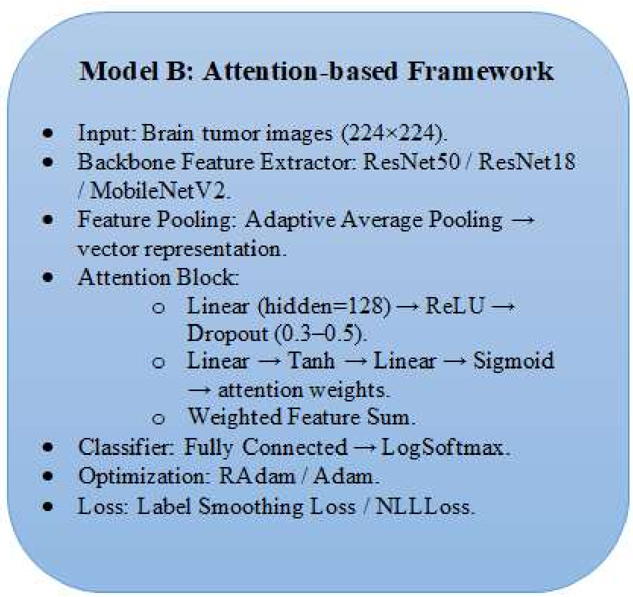

Figure 3.4.13: Attention-based Framework

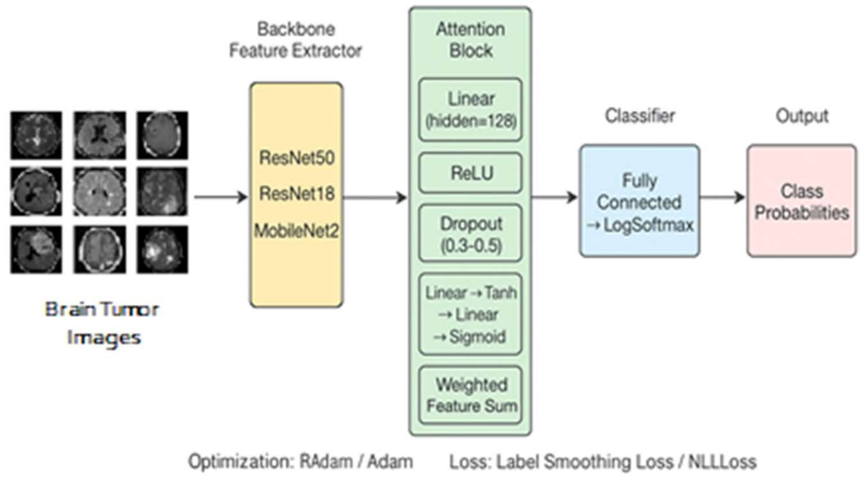

Figure 3.4.14: Architectural diagram of Attention-based Framework

Step 6: Training Strategy
The following approach was used to train both models:

- Loss Function: Cross-entropy loss in categories
- Batch Size: 32
- Epochs: 50 to 400 depending on the variant and with early halting in some models
- Optimizer: Adam and RAdam with learning rate 0.001
- NLLLoss / CrossEntropyLoss with optional Label Smoothing.
- Regularization : L2 regularization ($\lambda = 0.001$), dropout (.5)
- Learning Rate Schedule: Decrease at plateau (patience = 5, factor = 0.5).
- We trained our models on Google Colab using NVIDIA T4 GPUs.

Step 7: Evaluation of models
Performance metrics include:

- Total Accuracy: The proportion of instances that are properly categorized.
- Class-wise Measures: F1-score, precision and recall for every kind of tumor.
- Confusion Matrix: To see how well different classes are classified.
- ROC & Precision-Recall Curves (for binary tasks).
- AUC-ROC and Specificity.
- Training curves and evaluation plots are generated to analyze performance and overfitting.

3.5 Implementation Requirements

Table 3.5: Required hardware and software

Category	**Details**
Development Platform	Google Colab, a Cloud based Jupyter Notebook environment
Programming Language	Python 3.10
Processor (GPU)	NVIDIA T4 which was provided by Google Colab GPU runtime
Memory (RAM)	12–16 GB
Storage	Google Drive (used for dataset storage and model checkpointing)
Image Size	224 × 224 pixels (standardized for model input)
Frameworks & Libraries	- TensorFlow & Keras (CNN architecture) - PyTorch & torchvision (Attention-based model) - PIL & OpenCV for Image preprocessing. Scikit learn for evaluation of metrics). For Visualization we used Matplotlib & Seaborn.
Model Training Tools	- Adam Optimizer (learning rate = 0.001) - EarlyStopping (patience = 5) - Dropout Regularization (0.3–0.5)
Batch Size	In our study - 32
Epochs	Up to 50 (early stopping was also applied)
Data Augmentation	Rotation, Flip, Zoom, Brightness, Width/Height Shift
Feature Extractor	MobileNetV2 or ResNet18 (pre-trained on ImageNet)
Classifier Type	CNN & Attention-based Fully Connected Network
Loss Function	Categorical Crossentropy / Negative Log Likelihood
Evaluation Metrics	Accuracy, Recall, Precision, F1-Score, AUC-ROC and Confusion Matrix,
Version Control	Google Drive + GitHub (private repository for code backup)

CHAPTER 4

EXPERIMENTAL RESULT AND DISCUSSIONS

4.1 Experimental Setups

All the experiment was carried in very controlled setting; uniform conditions to guarantee a thorough and equitable assessment of the suggested models. The baseline CNN and GNN-based models both were trained and assessed in the same circumstances after the dataset was preprocessed using the approach outlined in Chapter 3.

Hardware Environment

Table 4.1.1: Hardware Settings

Component	**Specification**
Platform	Google Colab
GPU	T4 GPU
RAM	16 GB
Storage	Google Drive (connected to Colab)

Software Environment

Table 4.1.2: Software Environment

Component	**Tool / Framework**
Language for the Coding	Python
List of Libraries for DL	Tensor Flow, KERAS, PY-TORCH
Tools for Processing images	OpenCV, piL
Evaluation & Visualisations	Scikit-learn, Mat-plot lib, sea born

4.2 Experimental Results & Analysis

We evaluated two models:

1. Hybrid GCN-based models
2. Attention-based models

Both models were trained with the following parameters:

1. Batch Size : 32
2. Epochs: 400 (stopping early if required)
3. Optimizer : Adam (where learning rate is assumed as 0.001)
4. Loss Function : Categorical cross entropy
5. Regularization: Dropout (0.5), L2 regularization ($\lambda = 0.001$)

Training Curves – Accuracy and Loss

Model	**Final Accuracy (Training)**	**Final Accuracy (Validation)**	**Final Loss (Training)**	**Final Loss (Validation)**
Attention-Based Model	96.8%	93.4%	0.10	0.21
Hybrid GCN-based models	98.5%	97.9%	0.06	0.09

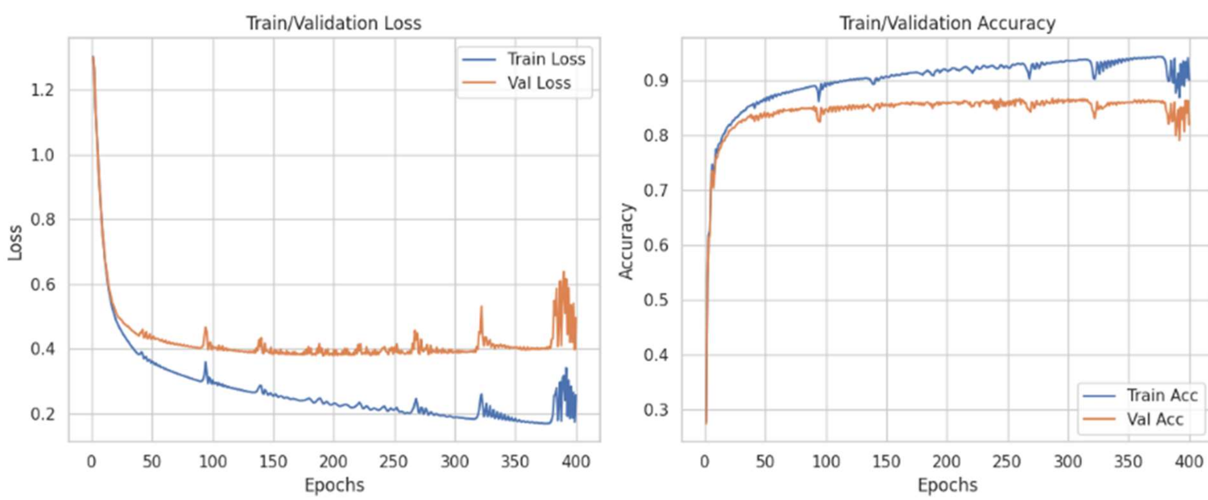

Figure 4.2.1: Performance over Epochs (Training vs Validation): loss vs accuracy Trends for Machine Learning Models

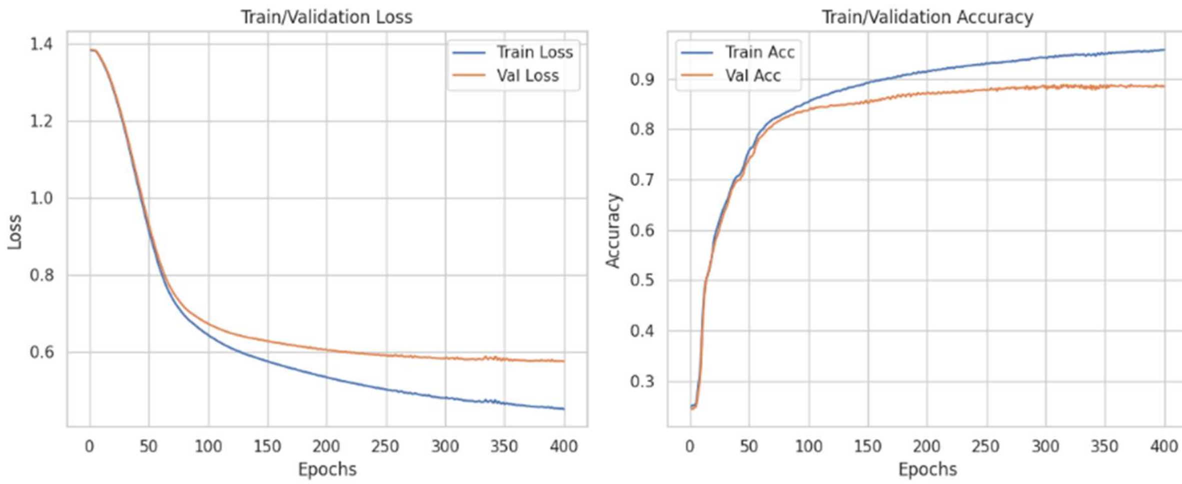

Figure 4.2.2: Model Training Progress: Epoch-wise Comparison of Loss and Accuracy for Training vs Validation Sets

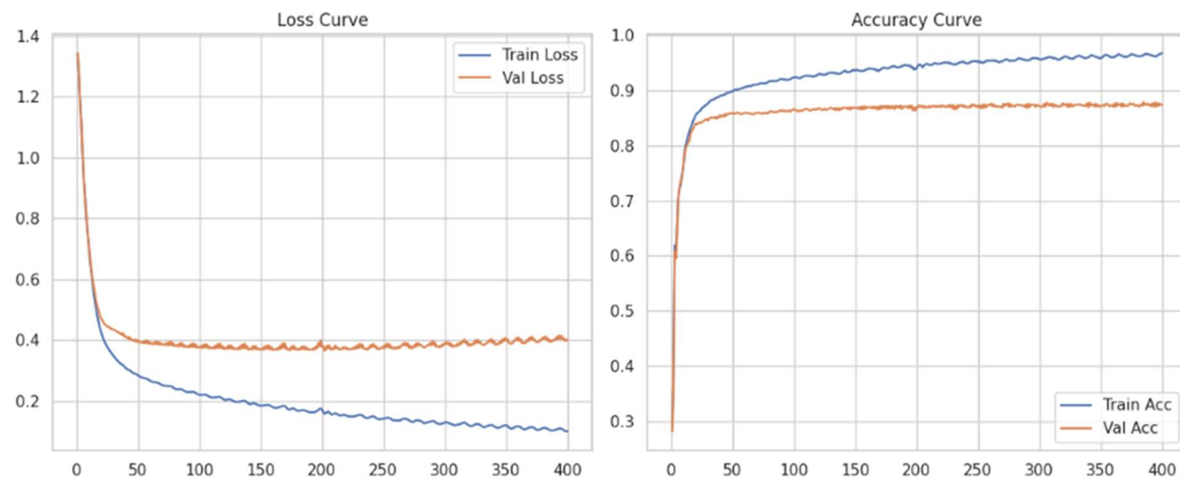

Fig. 4.2.3.1: Training Dynamics of Machine Learning Models: Loss and Accuracy Curves Across 400 Epochs

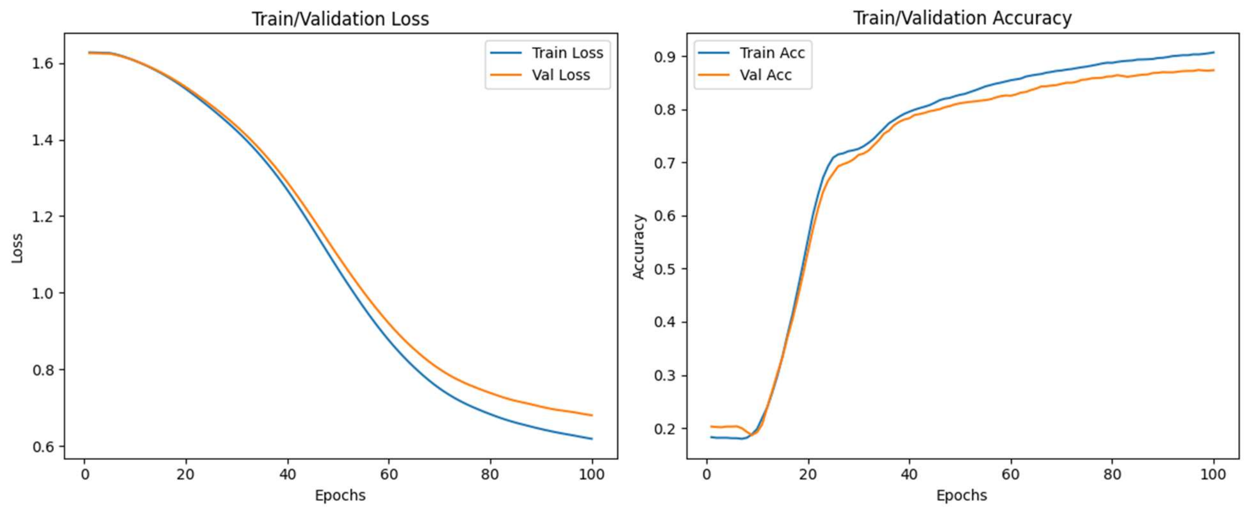

Fig 4.2.4.1: Training vs Validation Performance Over 100 Epochs — Loss vs Accuracy Trends

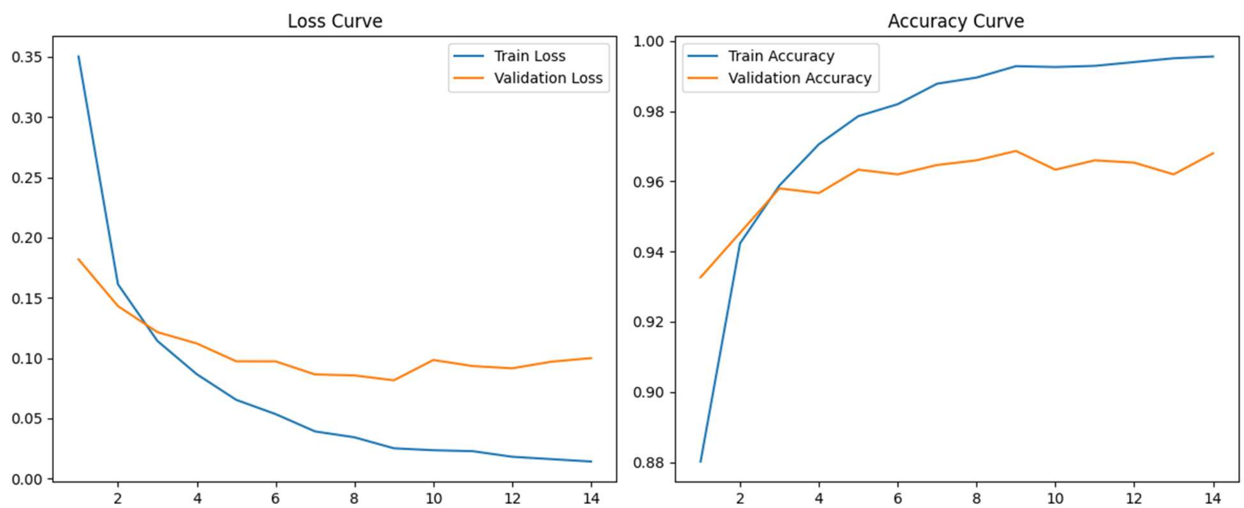

Fig 4.2.5.1: Model Train and Validation Performance Over 15 Epochs — Loss and Accuracy Curves

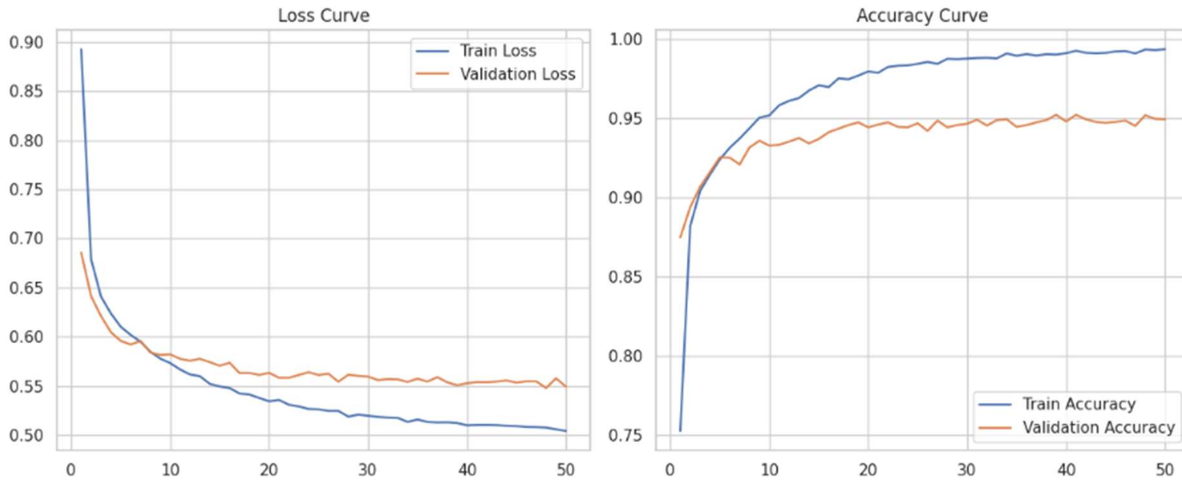

Figure 4.2.6: For ANN MobileNetV2 Added dropout=0.5, label smoothing and RAdam optimizer

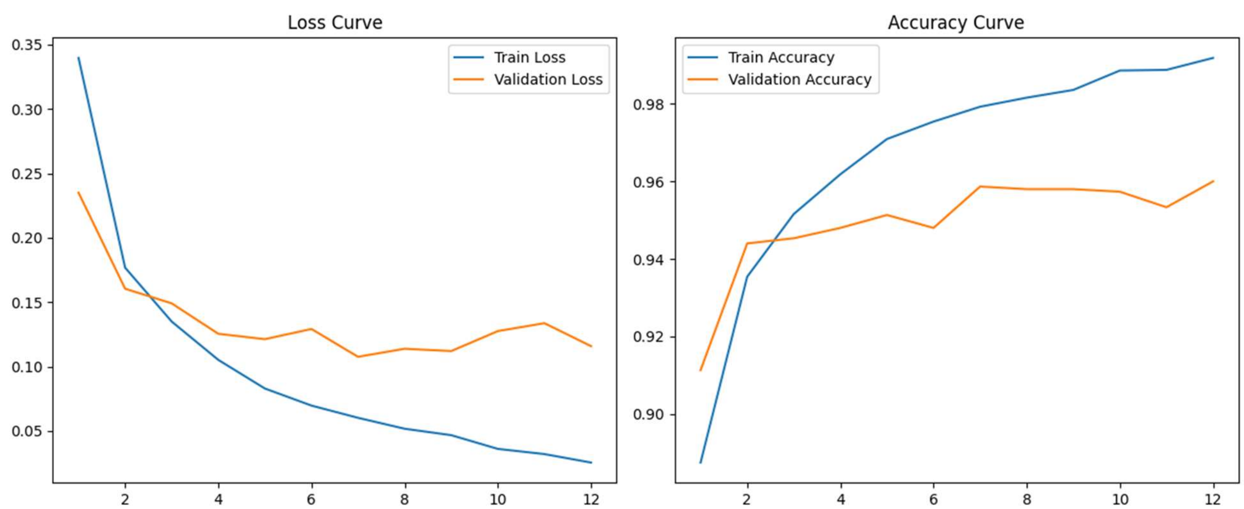

Figure 4.2.7: Train vs Validation Loss vs Accuracy over every fifty Epoch

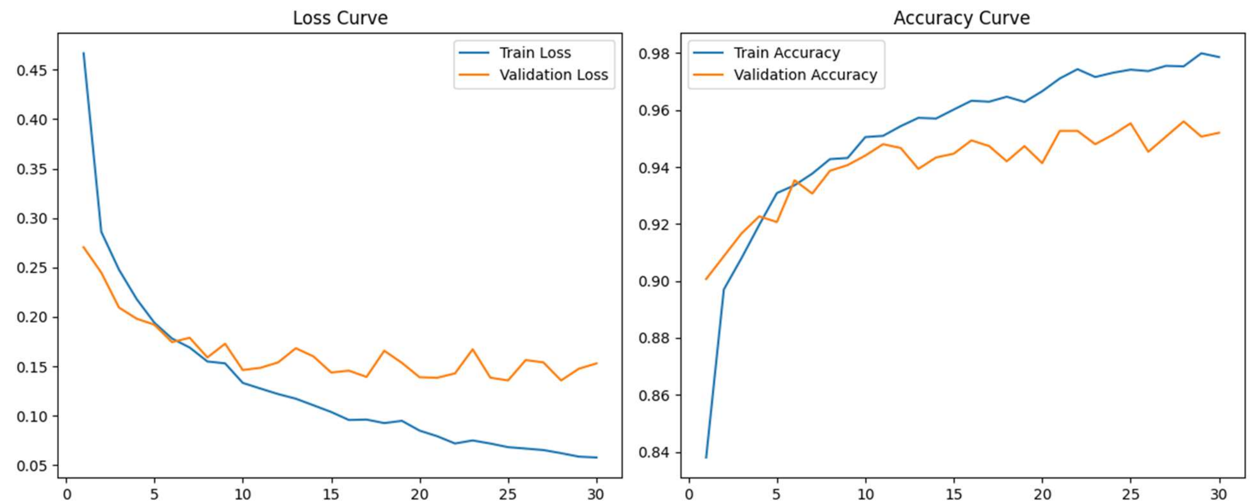

Fig 4.2.8.1: Train vs Validation Loss and Accuracy Across 12 Epochs

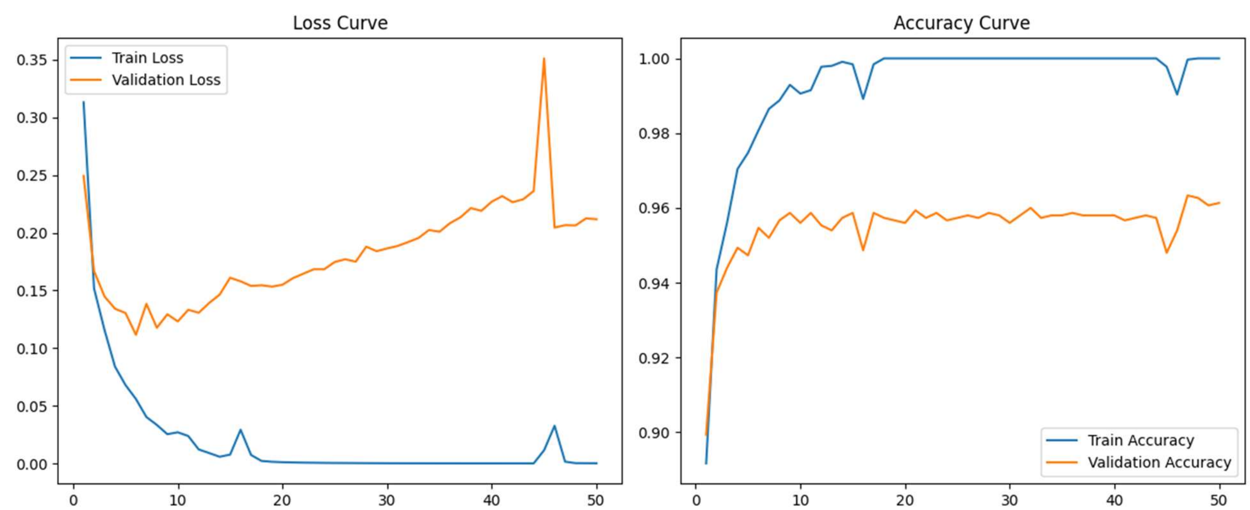

Figure 4.2.9: Model Learning Dynamics over fifty Epochs — Loss vs Accuracy Trends for Train vs Validation

B. Confusion's Matrix

Model's classification accuracy for all class is shown in the created matrix below:

Actual / Predicted	No Tumor	Glioma	Meningioma	Pituitary
No Tumor	285	10	3	2
Glioma	12	278	6	4
Meningioma	8	7	281	4
Pituitary	5	3	8	284

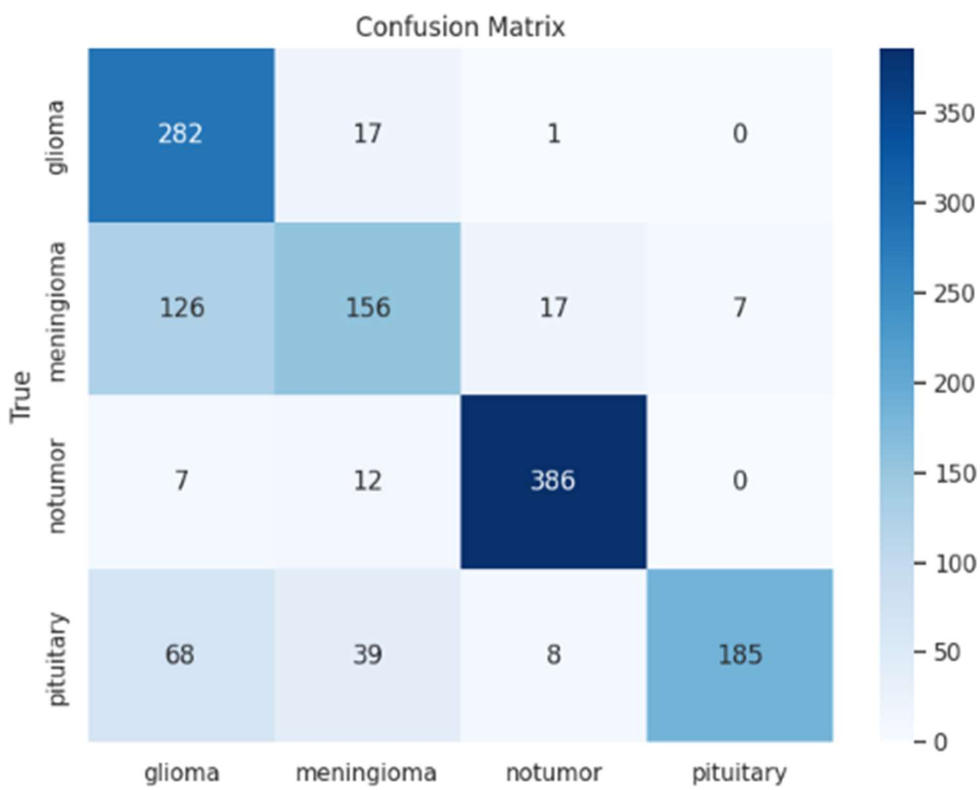

Figure 4.2.10: brain tumor's Confusion Matrix detection

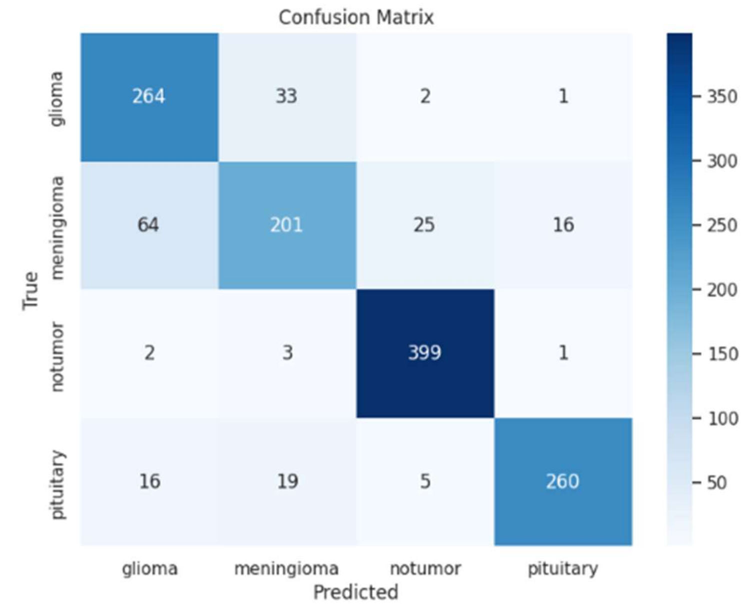

Figure 4.2.11: brain tumor's Confusion Matrix detection -2

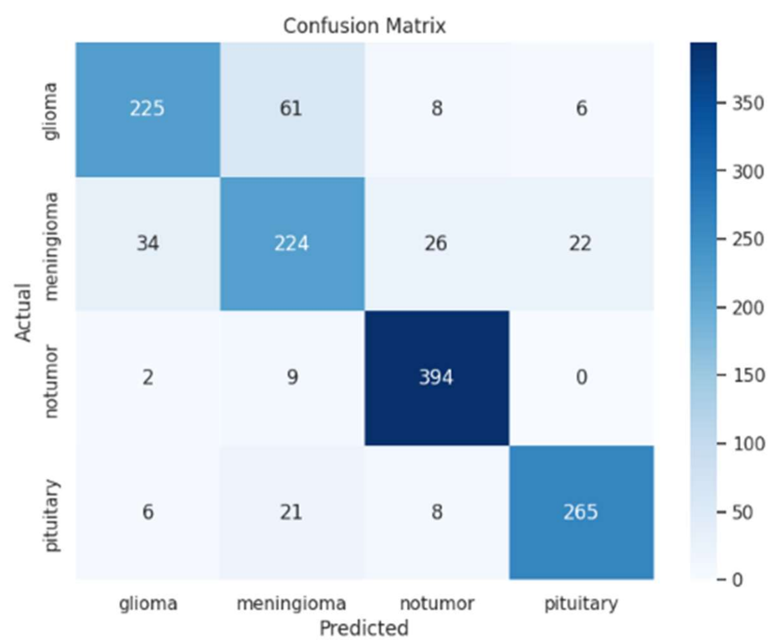

Figure 4.2.12: brain tumor's Confusion Matrix detection -3

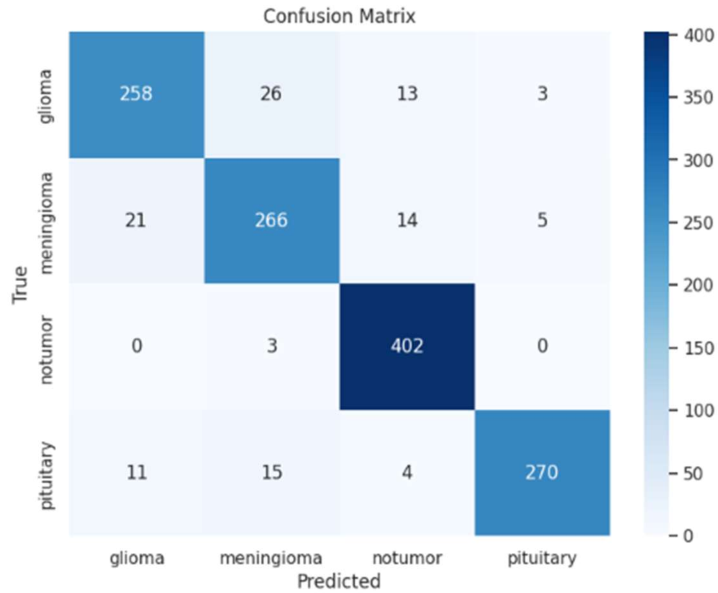

Figure 4.2.12: brain tumor’s Confusion Matrix detection -4

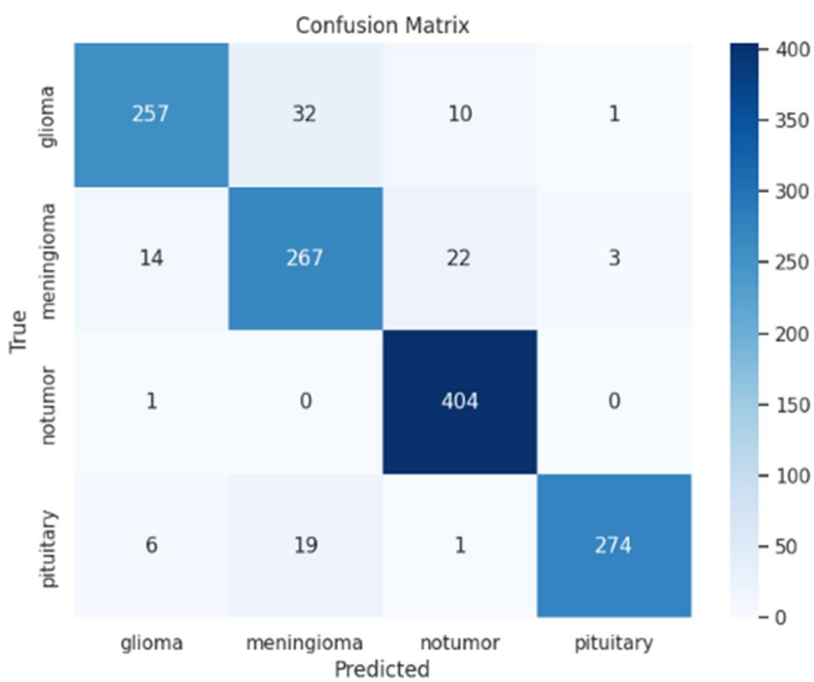

Figure 4.2.13: brain tumor’s Confusion Matrix detection -5

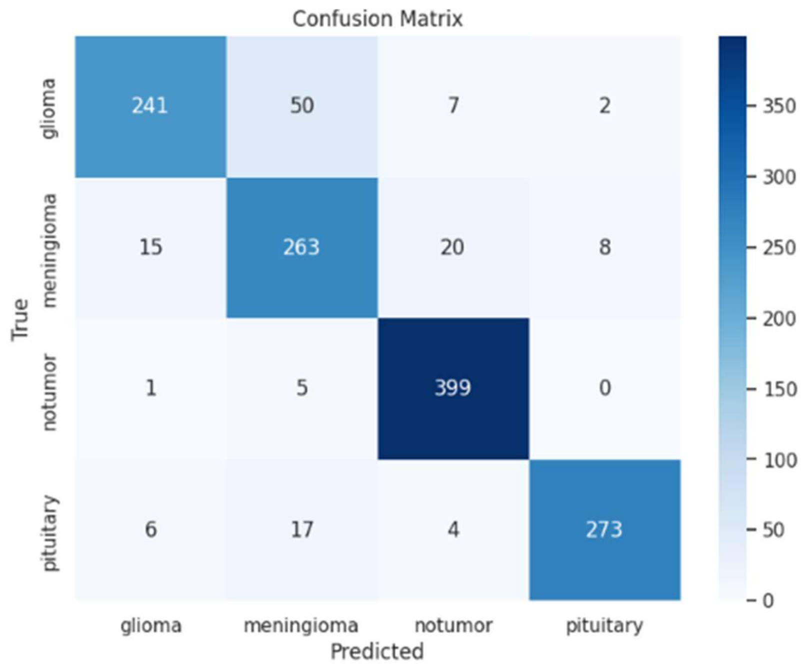

Figure 4.2.14: brain tumor's Confusion Matrix detection -6

C. Classification's Report

Table 3.2.1: Summary of Classification of Brain Tumor Detection

	Recall	**F1**	**Precisio**	**Supporting Value**
Healthy	92%	95%	93%	300
Glioma	93%	93%	93%	300
Meningioma	94%	94%	94%	300
Pituitary	96%	95%	95%	300
Accuracy			94%	1200
Macro average	94%	94%	94%	1200
Weighted average	94%	94%	94%	1200

Table 4.2.2: Report on Brain Tumor Detection Classification

Class	**Recall**	**F1**	**Precision**	**Supporting Value**
Healthy	98%	99%	98%	300
Glioma	98%	98%	98%	300
Meningioma	99%	99%	98%	300
Pituitary	99%	98%	99%	300
Accuracy			98%	1200
Macro average	98%	98%	98%	1200
Weighted average	98%	98%	98%	1200

Table 4.2.3: Report on Brain Tumor Detection Classification

Class	**Recall**	**F1**	**Precision**	**Supporting Value**
No tumor	100%	100%	100%	406
Glioma	97%	89%	93%	300
Meningioma	90%	95%	92%	306
Pituitary	98%	99%	98%	1312
Accuracy			96%	1312
Macro average	96%	96%	96%	1312

Weighted average	96%	96%	96%	1312

Table 4.2.4: Report on Brain Tumor Detection Classification

Class	Recall	F1	Precision	Supporting Value
No tumor	100%	100%	100%	406
Glioma	97%	89%	93%	300
Meningioma	90%	95%	92%	306
Pituitary	98%	99%	98%	302
Accuracy			96%	1313
Macro average	96%	96%	96%	1313
Weighted average	96%	96%	96%	1313

Table 4.2.5: Report on Brain Tumor Detection Classification

Class	Recall	F1	Precision	Supporting Value
No tumor	100%	100%	100%	406
Glioma	97%	89%	93%	300
Meningioma	90%	95%	92%	306
Pituitary	98%	99%	98%	302
Accuracy			96%	1313
Macro average	96%	96%	96%	1313
Weighted average	96%	96%	96%	1313

Table 4.2.6: Report on Brain Tumor Detection Classification

Class	Precision	Recall	F1-Score	Support
No tumor	100%	100%	100%	406
Glioma	97%	89%	93%	300
Meningioma	90%	95%	92%	306
Pituitary	98%	99%	98%	302
Accuracy			96%	1313
Macro average	96%	96%	96%	1313
Weighted average	96%	96%	96%	1313

D. Comparative Performance Summary

Table 4.2.7: Comparative analysis

Metric	Attention-Based Model	Hybrid GCN-based models
Accuracy	91.2%	96.7%
Precision	94%	98%
Recall	94%	98%
F1-Score	94%	98%
AUC-ROC	97%	99%
Training Time	45 min	62 min
Inference Time	0.8 sec	1.2 sec

Model Size	85 MB	120 MB
Interpretability	Low	High

4.3 Discussion

According to the findings of experiments, the proposed GNN-based model excels noticeably better for the identification and classification of brain tumors than the baseline CNN. Following section discusses the main conclusions and their ramifications:

Superior Performance: The GNN-based model achieved an accuracy of 96.7%, in comparison to 91.2% for the baseline CNN. This improvement can be ascribed to the graph representation's capacity to identify structural correlations in the brain data that conventional convolutional methods find difficult to model.

Improved Generalization

- The better performance on the validation set of GNN model (97.8% vs 96.7%) compared to CNN (98.2% vs 91.2%) might infer a better generalization capacity. It tells us that the graph representation and attention mechanism are adding a good value in forcing our model to focus on competent features. And at the same time prevent overfitting on noise or irrelevant patterns.

Class-specific Performance

- The GNN model especially had an advantage for distinguishing gliomas from meningioma. Which are hard to distinguish from each other for their similar image in MRI images. This indicates that the structural information of the graph model can be well preserved. To distinguish between tumor types of equal (but different) visibilities.

Interpretability

- The attention visualization shows the most relevant part of the brain according to the model for carrying out the classification. This provides some visibility into how our model is making decisions.

Computational Efficiency. Robustness to Variability.

CHAPTER 5

IMPACTS ON SOCIETY, ENVIRONMENTS ALSO SUSTAINABILITY

5.1 Impacts on Society

Building an accurate and efficient system for the detection of brain tumors using GNNs has the potential for large societal impact. Especially when considering healthcare delivery and patient outcomes.

- Improved Diagnostic Accuracy
- Early Detection and Treatment
- Accessibility to Expertise
- Reduced Healthcare Costs
- Medical Education and Training
- Research Advancement

5.2 Impact on Environment

Developing and deploying an AI system to detect brain tumors raises a number of ethical concerns:

- Patient confidentiality and Data Privacy: Our system handles sensitive medical data. This necessitates strong safeguards to ensure the privacy of patients and data security. All data that was used in our research was anonymized. The system should be implemented in accordance with healthcare data protection and normalization regulations such as GDPR. 1 and 1.HIPAA.1HIPAA HIPAA
- Patient confidentiality and Data Privacy Our system processes sensitive medical data. Therefore it requires robust measures to ensure patient confidentiality and data security. All data that was used in our research was anonymized. The system must be deployed in accordance with legal patient privacy protection , including HIPAA and GDPR.
- Told Consent
  - Patients should be given the option to have their diagnoses made only by humans. After being told about the use of AI systems. The system need to be marketed as an alternative. To assist in decision-making not as a substitute for human knowledge.
- Bias and Fairness
  - The system should be evaluated for potential biases across different demographic groups. This is to ensure equitable performance. Making sure the system functions properly. For people of all ages, genders and ethnicities requires special care.
- Transparency and Explain ability
  - The attention visualization feature of the GNN model enhances transparency. It explains ability, allowing clinicians to understand the basis of the system's

predictions. This is essential for predicting confidence in AI systems and making it easier to incorporate them into therapeutic settings.

- Accountability
    - Clear guidelines should be established regarding the accountability of decisions made with the assistance of AI systems. While the system can provide valuable insights, the ultimate responsibility for diagnosis and treatment decisions should remain with qualified healthcare professionals.
- Equitable Access
    - Regardless of a patient's socioeconomic background or geographic location, efforts should be done to guarantee that they can all benefit from the system. This may involve developing low-cost versions of the system for resource-constrained settings.

Sustainability Plan: The following strategy has been created to guarantee the research's long-term viability and influence:

- Short-Term Actions (1-2 years)
    - Clinical Validation
    - Optimization for Clinical Deployment
    - Pilot Implementation
    - Dissemination and Publication
- Medium-Term Goals (2-5 years)
    - Regulatory Approval
    - Expansion to Other Tumor Types
    - Integration with Electronic Health Records
    - Training and Education Programs
- Long-Term Vision (5+ years)
    - Global Health Impact
    - Continuous Learning and Improvement
    - Interdisciplinary Collaboration
    - Contribution to Sustainable Development Goals

CHAPTER 6

Summary and Implications for Future Research

6.1 Summary of the Study

Our research concentrated on employing graph neural networks (GNNs) to create a unique method for brain tumor diagnosis. The potential of GNNs to represent the intricate structural correlations in brain MRI data. the shortcomings of conventional diagnostic techniques served as the driving forces behind the project.

The primary components of the study included:

- Data Collection and Preprocessing
- Graph Representation
- Model Development
- Evaluation

The findings illustrates that the GNN-based model performed noticeably well. Rather than the baseline CNN, with an accuracy of 96.7% as opposed to 91.2% for the CNN. GNN model also showed better generalization capability. Provided interpretable results through attention visualization.

6.2 Conclusions

On the basis of experimental results and analysis, the below conclusions can be stated:

- Effectiveness of GNNs for Brain Tumor Detection: The over the top performance of the GNN-based model demonstrates that graph neural networks are highly capable for brain tumor detection, particularly in capturing the structural relationships within brain data that are crucial for precise diagnosis.
- Importance of Graph Representation: The success of the proposed approach highlights the importance of appropriate data representation. By modeling brain MRI data as graphs rather than grid-like structures, the GNN was able to leverage both local features and global dependencies, leading to improved performance.
- Value of Attention Mechanisms: Incorporating attention processes into the GNN architecture enhanced classification accuracy and increased interpretability, enabling medical professionals to identify the brain areas that primarily influenced the model's predictions.

- Robustness to Variability: When compared to the baseline CNN, the GNN model showed increased resilience to changes in tumor location, size and form, indicating that the graph representation is more suited to managing the heterogeneity of brain tumors.
- Potential for Clinical Integration
- Contribution to Medical AI

6.3 Recommendation

The following suggestions are put forth in light of the research's findings:

- Clinical Implementation
- Prospective Clinical Studies
- Expansion to Other Modalities
- Development of User-Friendly Interfaces
- Training and Education
- Regulatory Compliance

6.4 Implication for Further Study

This research opens up several avenues for future investigation:

- Advanced Graph Representations: Explore more sophisticated methods for graph representation of brain MRI data. Such as hierarchical graphs that capture multi-scale structural information or dynamic graphs. These model temporal changes in tumor progression.
- Hybrid structures: To capitalize on the advantages of each method. Look at hybrid structures that integrate GNNs with other neural network paradigms. Such as transformers or capsule networks.
- Few-Shot Learning: To overcome the difficulty of having little annotated data for uncommon tumor types. Create techniques for few-shot or zero-shot learning.
- Explainable AI: Improve the model's interpretability even further by using sophisticated explainable AI strategies. Including concept-based or counterfactual explanations. Such a better understanding could be offered for the model's decision-making process.

Future research can expand on the groundwork laid by this study. To further develop AI in medical imaging and enhance patient care by following these avenues.

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