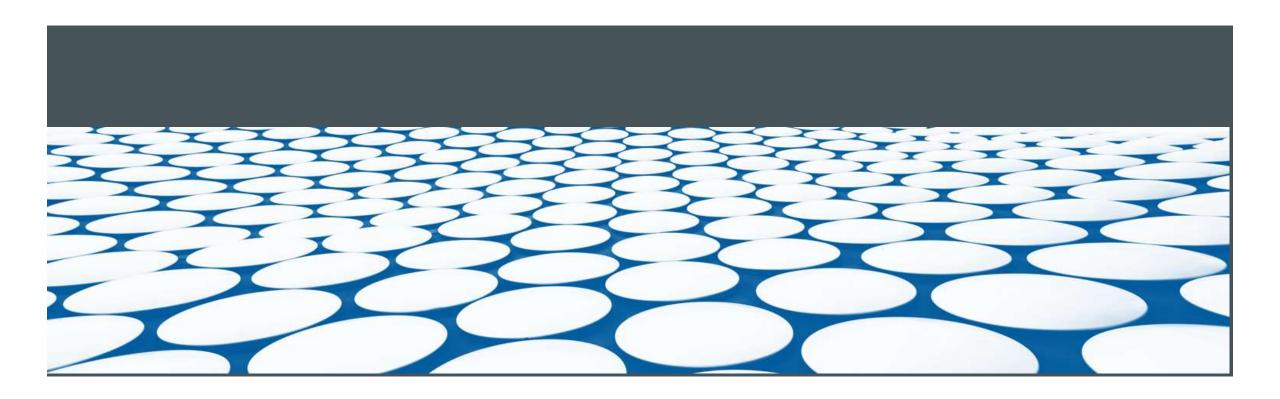
# 5502 GROUP #1 MIDTERM REPORT

# BRAIN TUMOR CLASSIFICATION USING CNNS AND GRAD-CAM



### 1. Introduction

### Objectives

- Develop an automated CNN model for accurate brain tumor classification.
- Enhance image interpretability using CLAHE (Contrast Limited Adaptive Histogram Equalization).
- Evaluate model performance with metrics such as accuracy, precision, recall, and F1-score.
- Incorporate Grad-CAM to visualize regions contributing to predictions, ensuring clinical explainability.

# 2. Dataset Description - Data Source

#### Data Source:

The dataset consists of MRI scans from Kaggle, organized into:

- Training Set: Contains labeled images (5,712 samples) across four categories.
- Testing Set: Contains 1,311 images for validation.

#### Classes:

- Glioma: Tumors arising from glial cells.
- Meningioma: Tumors originating in the meninges.
- Pituitary: Tumors in the pituitary gland.
- No Tumor: Normal brain scans.

# 2. Dataset Description - Data Distribution

Class	Training Samples	Testing Samples
Glioma	1,321	300
Meningioma	1,339	306
No Tumor	1,595	405
Pituitary	1,457	300

## 3. Model Architecture

#### CNN Structure

The CNN consists of the following layers:

- Convolutional Blocks:
  - Three blocks of Conv2D + MaxPooling + Dropout for feature extraction.
  - Filters:  $32 \rightarrow 64 \rightarrow 128$ .
  - ReLU activation.
- Dense Layers:
  - Flatten layer to transition from spatial to dense features.
  - Fully connected layers (128 neurons) with Dropout (0.5) for regularization.
  - Softmax output for 4-class classification.

**Loss Function:** sparse\_categorical\_crossentropy

Optimizer: Adam Metrics: Accuracy

# 4. Methodology

#### Preprocessing Steps

- **Grayscale Conversion**: RGB  $\rightarrow$  Single-channel for efficiency.
- Resizing: All images standardized to 150×150 pixels.
- CLAHE Enhancement: Adaptive contrast improvement.
- Normalization: Pixel values scaled to (0, 1).

## Model Training

**Epochs**: 10

**Batch Size:** 32

Validation Split: 20% held-out for validation.

# 5. Results – Training Performance

Epoch	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
1	54.12%	68.73%	1.0588	0.6899
10	95.78%	93.59%	0.1186	0.1685

#### Final Test Metrics:

• Overall Accuracy: 94%

Precision (Macro Avg): 0.94

• Recall (Macro Avg): 0.93

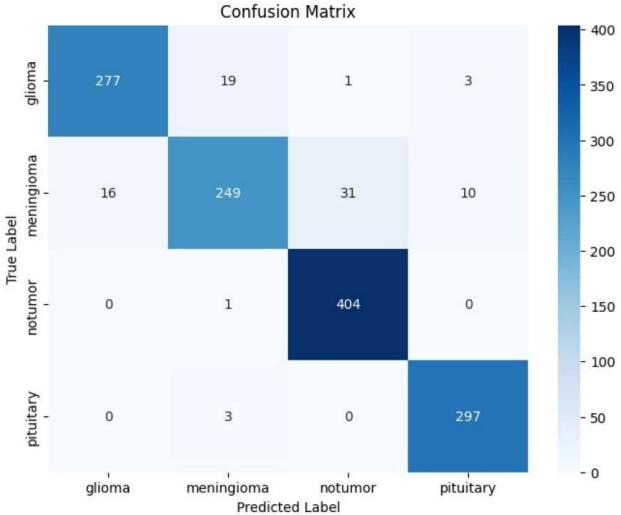
• F1-Score (Macro Avg): 0.93

# 5. Results – Class-Specific Performance

Class	Precision	Recall	F1-Score	Support
Glioma	0.95	0.92	0.93	300
Meningioma	0.92	0.81	0.86	306
No Tumor	0.93	1.00	0.96	405
Pituitary	0.96	0.99	0.97	300

# 5. Results - Confusion Matrix

**Key Observation:** Meningioma had lower recall (81%), with some confusion with glioma and no-tumor classes.



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# 6. Visualizations - Accuracy & Loss Curves

# Training Curves

No Overfitting: Validation accuracy closely follows training accuracy.

### Grad-CAM Interpretability

#### Grad-CAM Output

- The model accurately identifies tumor-localized regions.
- Highlights model transparency in clinical decision-making.

# 7. Interpretation and Discussion

## **Key Findings**

- The CNN achieved 94% accuracy, demonstrating strong generalization.
- Grad-CAM confirmed that the model focuses on medically relevant regions for classification.
- Meningioma misclassifications suggest potential areas for improvement.

# Challenges & Solutions

Challenge	Solution
Low contrast in MRI scans	CLAHE enhancement improved feature visibility.
Class imbalance	Future work could incorporate weighted loss or augmentation.
Model explainability	Grad-CAM helps build clinician trust.

## 8. Conclusion

This project developed an accurate (94%) and interpretable CNN model for brain tumor classification. Key contributions include:

- Preprocessing with CLAHE for improved image quality.
- Robust CNN architecture with regularization to prevent overfitting.
- Grad-CAM explanations for clinical interpretability.

#### **Future Work:**

- Data Augmentation for better meningioma recall.
- Transfer Learning with ResNet/VGG for higher accuracy.
- Larger, multi-center datasets for improved generalizability.

## 9. References

- 1. Selvaraju, R. R., et al. "Grad-CAM: Visual Explanations from Deep Networks." *ICCV 2017.*
- 2. CLAHE: <a href="https://docs.opencv.org/3.4/d5/daf/tutorial-py-histogram-equalization.html">https://docs.opencv.org/3.4/d5/daf/tutorial-py-histogram-equalization.html</a>
- 3. Dataset Source: Kaggle Brain Tumor MRI Dataset. <a href="https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset">https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset</a>

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