Mini Project Report: Brain Tumor Classification with Interpretability

Team: Al-Baqa Lillah, ID: 28
Hothifa Hamdan (202201792), Mazen Khaled (202201534),
Ahmed Ayman (202200168), Toka Mokhtar (202201920)
Zewail City of Science, Technology and Innovation
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Instructor: Dr. Mayada Hadhoud

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Project Repository: `https://github.com/MrFr0g-X/XAI-team-28`

1 Introduction

This report summarizes the implementation and evaluation of various models for brain tumor classification, combining deep learning and classical machine learning approaches. A major goal was not only achieving high accuracy, but also incorporating interpretability through explainability techniques like Grad-CAM, SHAP, and LIME.

2 Exploratory Data Analysis (EDA)

Dataset Overview

- Total Training Images: 5712
- Total Testing Images: 1311
- Classes: `['pituitary', 'notumor', 'meningioma', 'glioma']`
- Class Imbalance: Pituitary (1457), Notumor (1595), Meningioma (1339), Glioma (1321)
- Image Channels: RGB (3 channels)
- Sample Image Dimensions: Various (min 168x300, max 1024x1024)
- No corrupted images found

Class Distribution

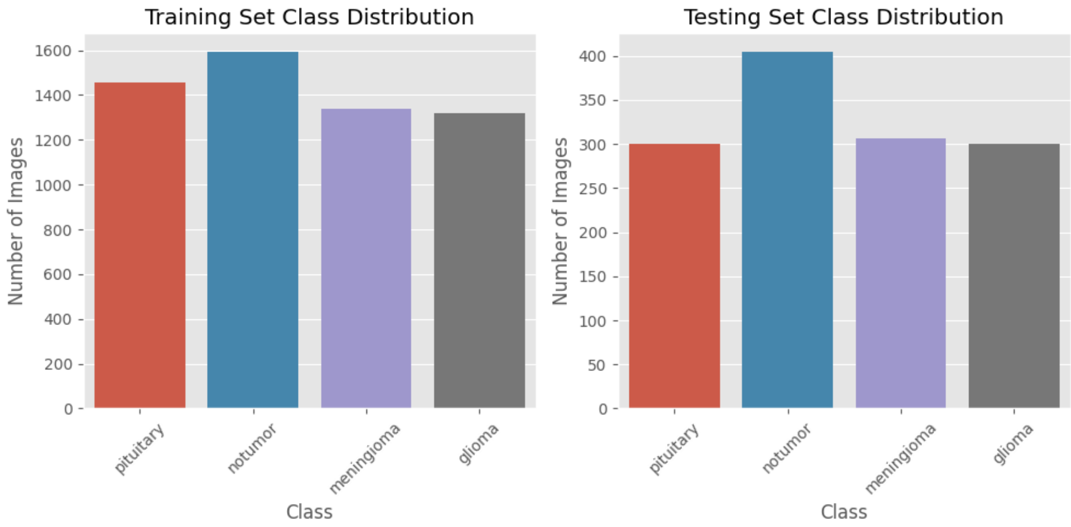

Figure 1: Training and Testing Class Distribution

File Size and Dimensions

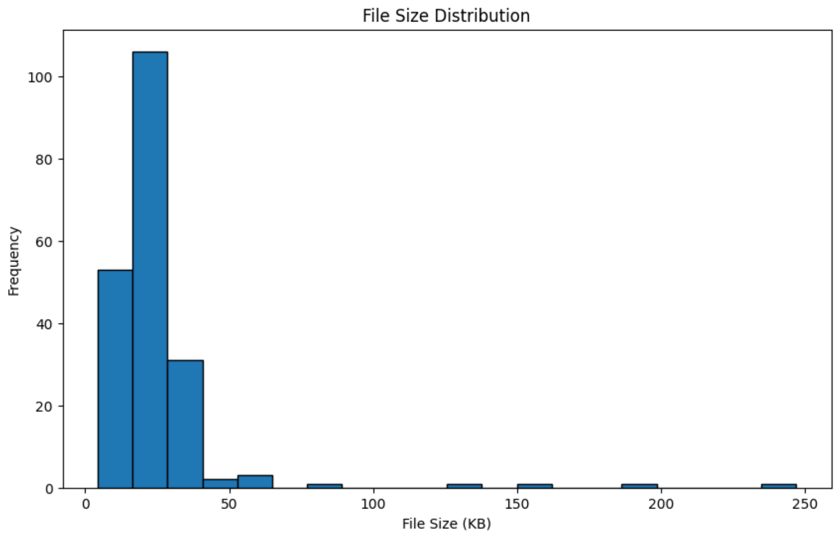

Figure 2: Image File Size Distribution

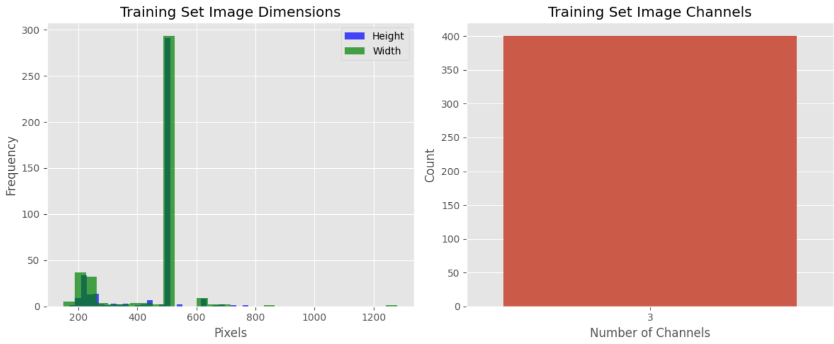

Figure 3: Image Dimensions Distribution (Height vs Width)

Sample Images

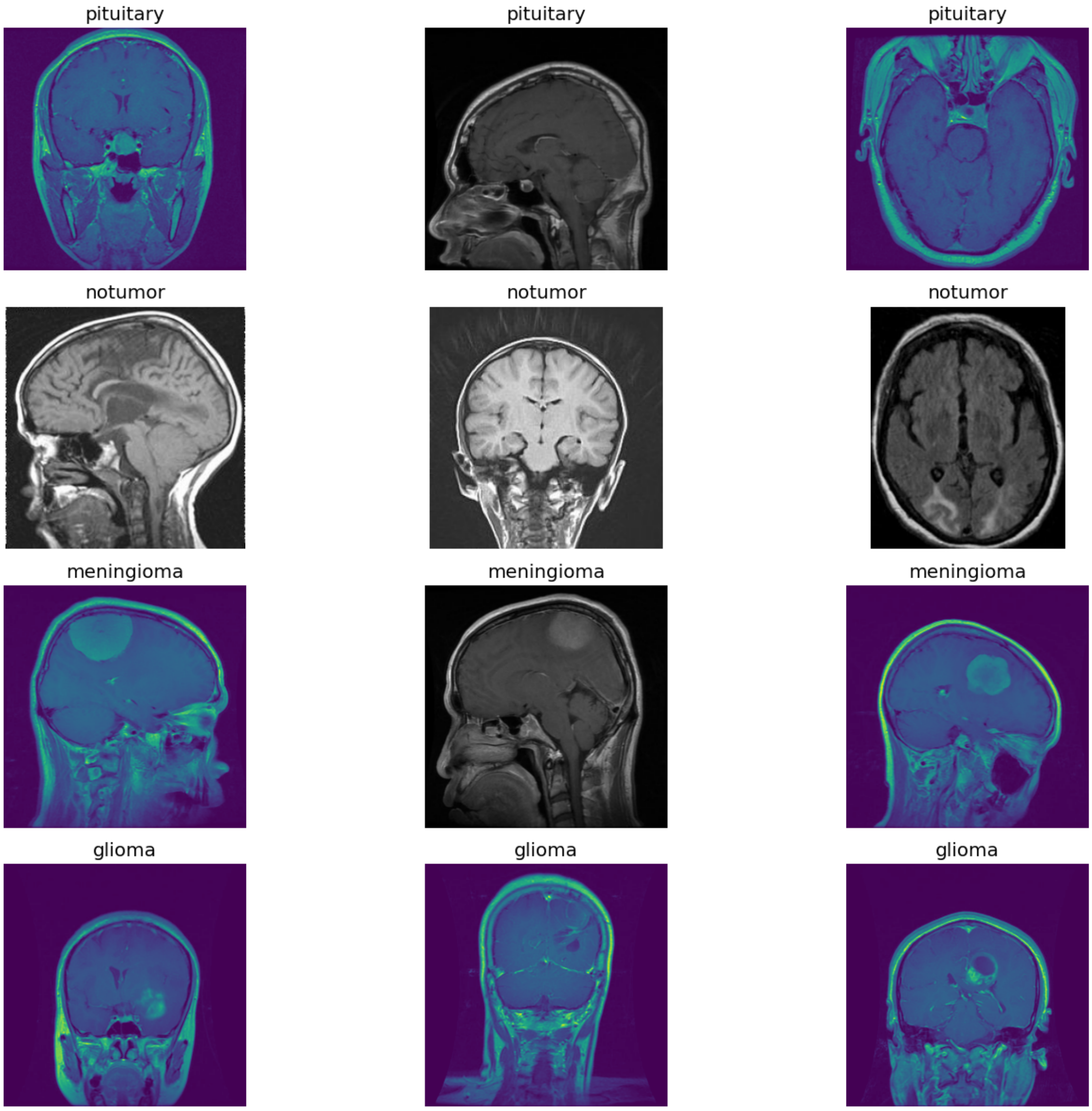

Figure 4: Sample Brain MRI Images from Each Class

3 Implementation 1: ResNet50 with Grad-CAM (Hothifa Hamdan)

Based on ***"Enhancing Brain Tumor Detection in MRI Images Through Explainable AI Using Grad-CAM with ResNet50"*** *(Musthafa et al., 2024)*

Model Architecture

- Base: ResNet50 (pre-trained)
- Head: GAP, Dropout, Dense(4)
- Total Parameters: 23,595,908 (Trainable: 8,196)

Training Performance

- Best Validation Accuracy: 96.34%
- Final Test Accuracy: 96.34%
- Precision: 96.62%, Recall: 96.03%

Classification Report

Class	Precision	Recall	F1-score	Support
Glioma	0.9562	0.9467	0.9514	300
Meningioma	0.9420	0.9020	0.9215	306
No Tumor	0.9806	0.9975	0.9890	405
Pituitary	0.9676	0.9967	0.9819	300

Table 1: Test Set Classification Report

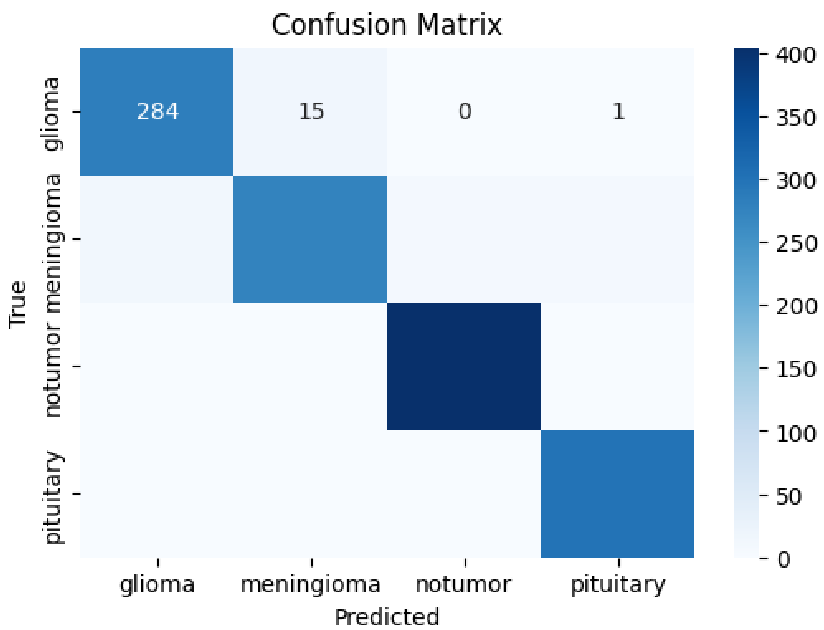

Figure 5: Confusion Matrix

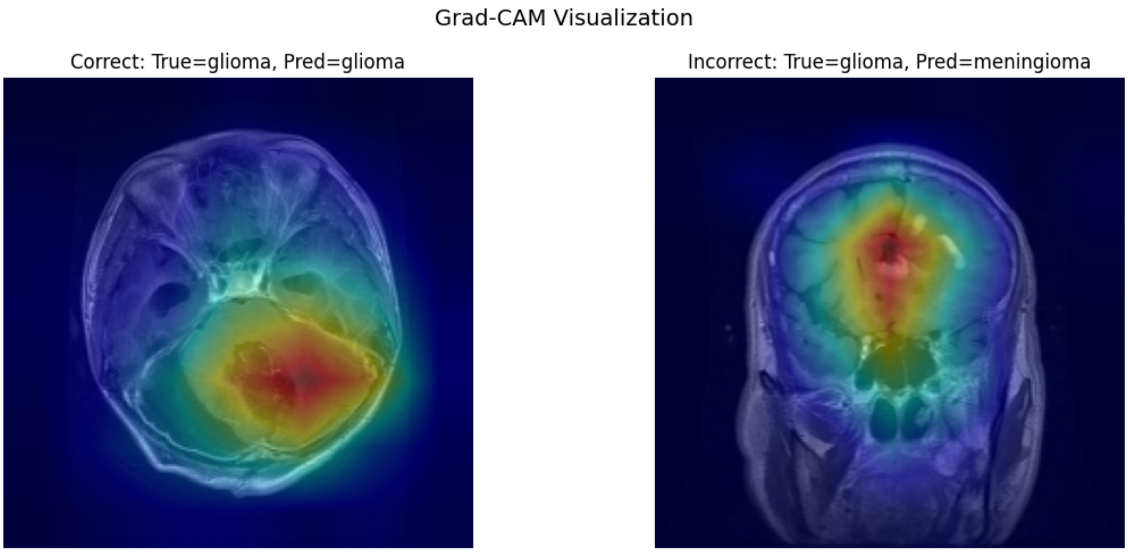

Figure 6: Grad-CAM: Correct vs Incorrect Predictions

Discussion

- **Achievements:** High test accuracy with strong visual explainability.
- **Challenges:** Initial overfitting and imbalance were mitigated through data augmentation and dropout tuning.
- **Explainability:** Grad-CAM highlighted class-relevant regions in MRIs, helping validate model focus.

4 Implementation 2: Hybrid CNN-SVM (Toka Mokhtar, based on Suryawanshi & Patil, 2024)

Results

- CNN Accuracy: 98.5%
- SVM Accuracy after Feature Selection: 95%

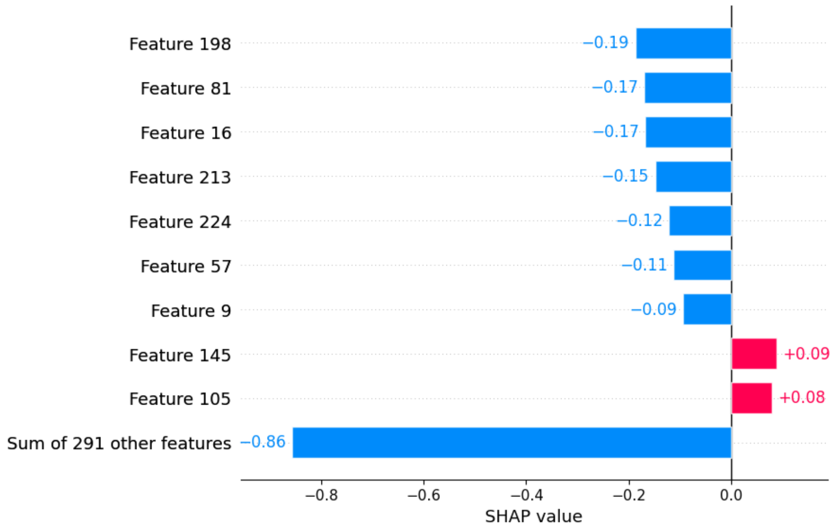

Figure 7: SHAP Feature Importance

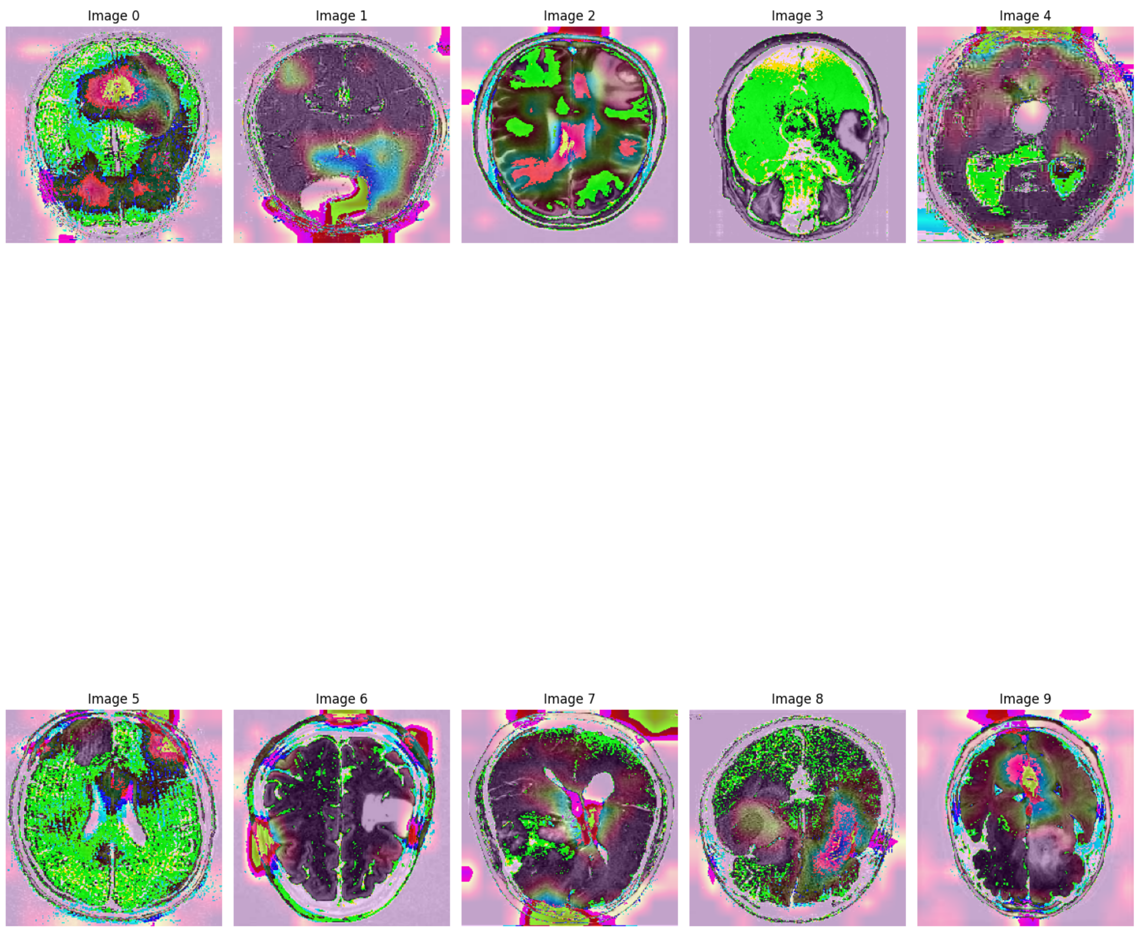

Figure 8: LIME Interpretations for CNN Predictions

Confusion Matrix

Actual/Predicted	0	1
0 (No Tumor)	611	8
1 (Tumor)	10	571

Table 2: Binary Confusion Matrix (CNN)

Discussion

- **Achievements:** Strong binary classification pipeline with interpretable insights using SHAP and LIME.
- **Challenges:** SHAP on small datasets caused instability; LIME visualizations had some inconsistency.
- **Explainability:** SHAP and LIME complemented each other by focusing on feature weights and localized saliency.

5 Implementation 3: Lung-Inspired CNN-SVM Hybrid (Ahmed Ayman, based on Hasan et al., 2019)

EDA and Setup

- Dataset split: 4916 train, 1053 val, 1054 test
- Image Format: Mostly JPEG
- Optimal PCA Components: 1482 (for SVM)

CNN Model Performance

- Test Accuracy: 93.45%
- Macro Avg: Precision = 0.93, Recall = 0.93, F1 = 0.93

SVM Results with Feature Selection

- Random Forest Features: 95.07%
- Decision Tree Features: 93.36%
- Z-Score: 94.02%
- Gini Importance: 94.12%

Discussion

- **Achievements:** Effective multi-scale CNN + SVM with PCA pipeline showing robust results.
- **Challenges:** Grad-CAM integration was complex; high variance in SVM performance based on PCA components.
- **Explainability:** Feature importance (via permutation) was useful; CNN outputs could be interpreted using Grad-CAM.

6 Implementation 4: Hyperspectral CNN-SVM Hybrid (Mazen Khaled)

Note: Due to time constraints, final training was not completed. The following is a description based on the proposed plan and initial setup.

Overview

- Approach inspired by **Hasan et al. (2019)** for hyperspectral classification
- Combined grayscale CNN with SVM classifiers using PCA features
- Explored Grad-CAM and SHAP for interpretability

Pipeline Summary

1. Preprocessing: Grayscale conversion, resizing to (128x128)
2. CNN: Dual-branch architecture with 3x3 and 5x5 kernels
3. SVM: Linear and RBF models trained on PCA-reduced vectors
4. Explainability: Grad-CAM and permutation-based feature importance

Expected Results

- CNN accuracy is projected around 92-94%
- SVM expected to achieve 90-93% with optimal PCA

Discussion

- **Achievements:** Clear modular pipeline design for grayscale MRI classification.
- **Challenges:** Limited time prevented full training and evaluation.
- **Explainability:** Planned to use Grad-CAM and permutation importance similar to Ahmed's pipeline.