Glioma-meningioma tumor classification on MRI scans

Written By: Nikolaos Mouzakitis

Date Last Edited: May 8, 2025

Abstract

This report presents an automated system for classifying brain tumors as either meningioma or glioma using MRI images. In the followed approach radiomic features from PyRadiomics with custom-designed intensity, shape, symmetry, and frequency domain features are blended together in order to train machine learning models for classification purposes. Two classifiers, Random Forest and Multi-Layer Perceptron (MLP) Neural Network) are evaluated. Feature extraction was performed using SimpleITK for image loading, OpenCV for preprocessing, and scikit-learn for modeling. Results showed that both models achieved good performance, with Random Forest outperforming the neural network slightly in terms of accuracy and AUC, demonstrating the feasibility of using hybrid feature engineering for medical image classification.

Contents

Chapter 1

Introduction

Brain tumors are among the most complex and dangerous diseases affecting the central nervous system. Early and accurate diagnosis is crucial in order to achieve effective treatment on time. Magnetic Resonance Imaging (MRI) is a widely used modality for detecting and characterizing brain tumors due to its high resolution and contrast.

Meningiomas and gliomas are two of the common types of primary brain tumors with different prognoses and treatment strategies. Manual differentiation by radiologists can be time-consuming and subject to variability. One solution for supporting clinical decision making, is an automated classification system. A system like this, can reduce diagnostic workload, increase consistency, and potentially improve early detection rates. It also provides a framework for future research into AI-assisted diagnostics in radiology or related application domains.

In this project, a machine learning-based system that automatically classifies MRI images into meningioma or glioma categories using custom handcrafted, frequency and radiomic features is developed and evaluated.

Chapter 2

Related Work

Chapter 3

Methodology-Implementation

3.1 Hw and Sw Requirements

The software stack used to implement the classification system consists of Python libraries such as *SimpleITK, OpenCV, scikit-learn, PyRadiomics, matplotlib, seaborn.*

3.2 Data Details

MRI images were sourced from [1], which contains 7023 MRI images of human brain, divided in 4 categories: *glioma - meningioma - no tumor and pituitary.* For this report's purpose the first two categories are utilized, and selected 1000 MRI images from both *glioma* and *meningioma* classes.

3.3 Method

Related to the methodology of the classification system, for the preprocessing step all images are loaded using SimpleITK and converted into NumPy arrays and their respective pixel intensities are normalized into the range of grayscale images ([0, 255]). In the next step a 4 pixel masking takes place, in order to reduce the black surrounding areas appearing in every MRI image. This border mask is applied and excludes irrelevant regions at the edges of the images. The number of the extracted features can be divided into three subcategories:

1)*Features acquired from Pyradiomics(*: by utilization of PyRadiomics first-order statistics (mean, variance, entropy) and texture features (GLCM, GLRLM, GLSZM) are extracted.
2)*Custom Features*: have been designed and implemented in order to in-

tuitively help detecting a tumor alike object on an MRI image. (*intensity_skewness, intensity_outlier_score, high_intensity_area, max_circularity, top3_circularity_mean, solidity_outlier, abnormal_area_ratio, circular_area_score, asymmetry_score, asymmetry_outlier, boundary_sharpness_mean, boundary_sharpness_max, boundary_sharpness_outlier*.

3)*Frequency Domain Features*: Energy, entropy, mean, and skewness in low, mid, and high-frequency bands using FFT.

By conducting the feature extraction process, *min-max* normalization is performed in all the generated feature values mapping them on the [0, 1] range.

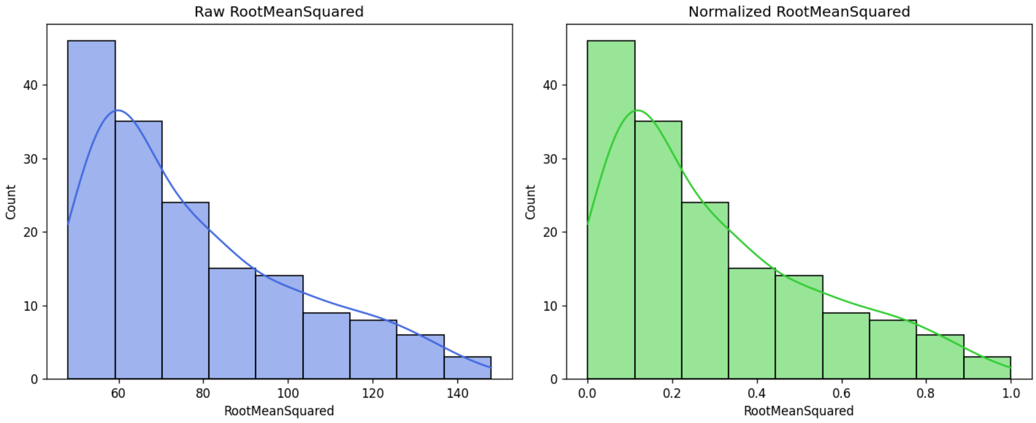

Figure 3.1: Comparisson of feature distribution prior and after the *min-max* normalization.

3.4 Evaluation Measures

In the classification stage, two different classifiers have been trained and evaluated, a Random Forest classifier and a MultiLayer Perceptron Neural Network.

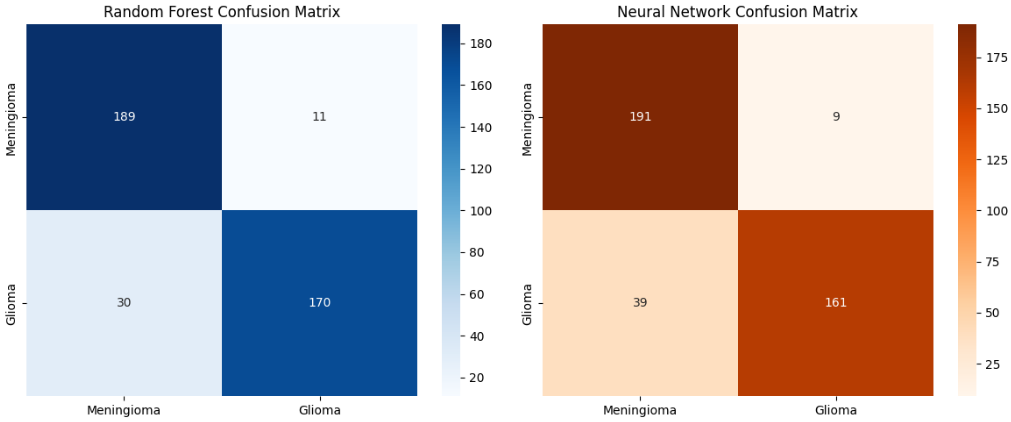

Figure 3.2: Metric results.

3.4.1 Classification with texture, shape and statistical features

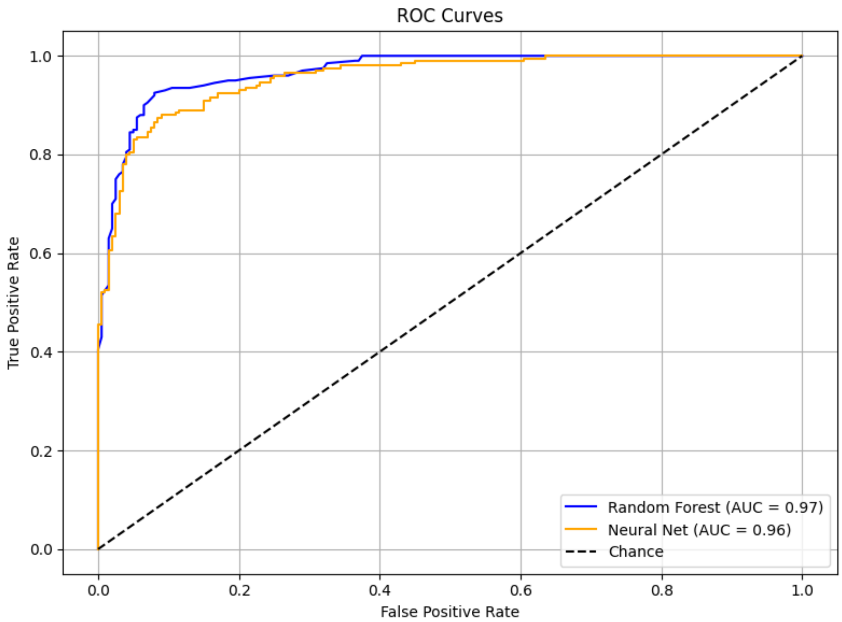

Figure 3.4: RoC curves for RF and MLP-nn.

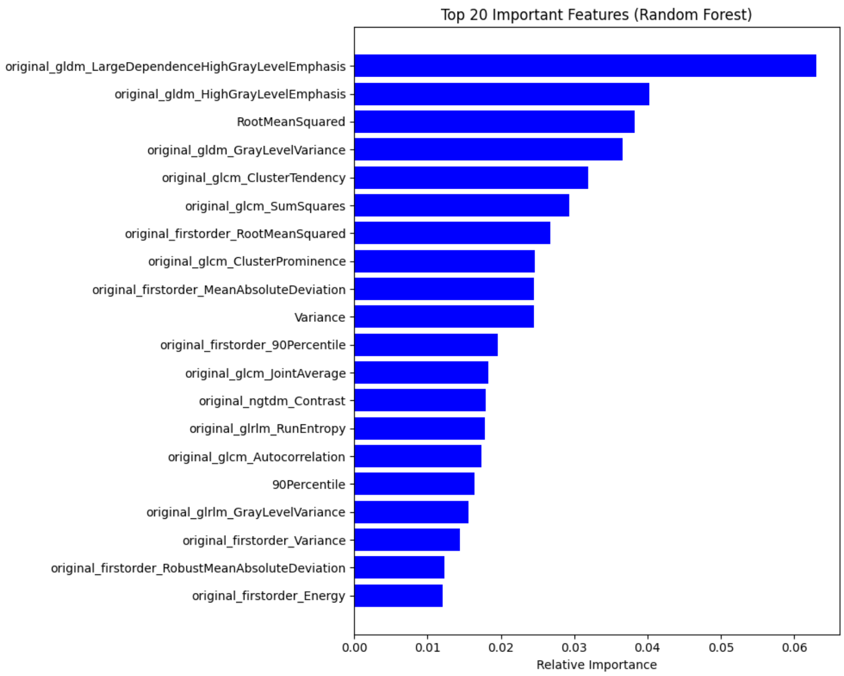

Figure 3.3: Top20 features of RF.

```
Training Random Forest...

Random Forest Results:
Accuracy: 0.897
AUC: 0.898

Classification Report:
              precision    recall  f1-score   support

           0       0.86      0.94      0.90       200
           1       0.94      0.85      0.89       200

    accuracy                           0.90       400
   macro avg       0.90      0.90      0.90       400
weighted avg       0.90      0.90      0.90       400


Training Neural Network...

Neural Network Results:
Accuracy: 0.880
AUC: 0.880

Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.95      0.89       200
           1       0.95      0.81      0.87       200

    accuracy                           0.88       400
   macro avg       0.89      0.88      0.88       400
weighted avg       0.89      0.88      0.88       400
```

Figure 3.5: Classification report

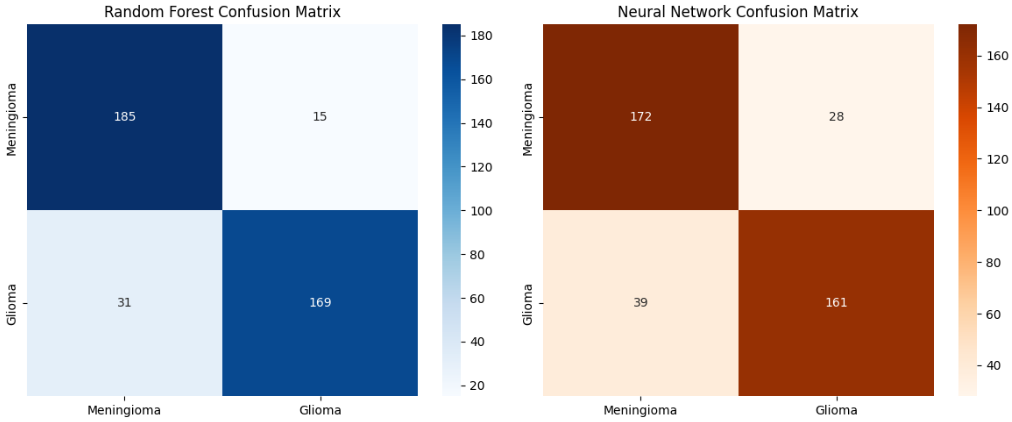

Figure 3.6: Metric results.

3.4.2 Classification with frequency features

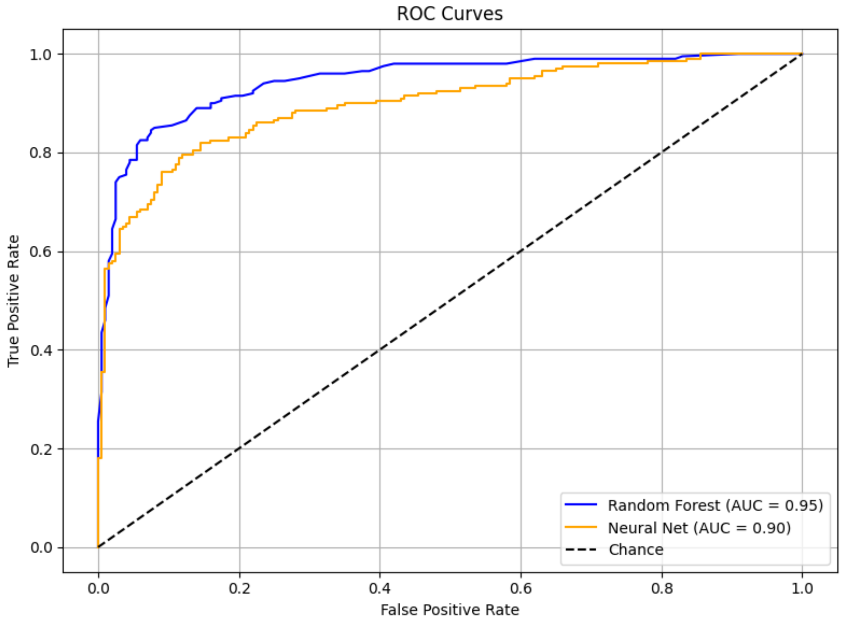

Figure 3.8: RoC curves for RF and MLP-nn.

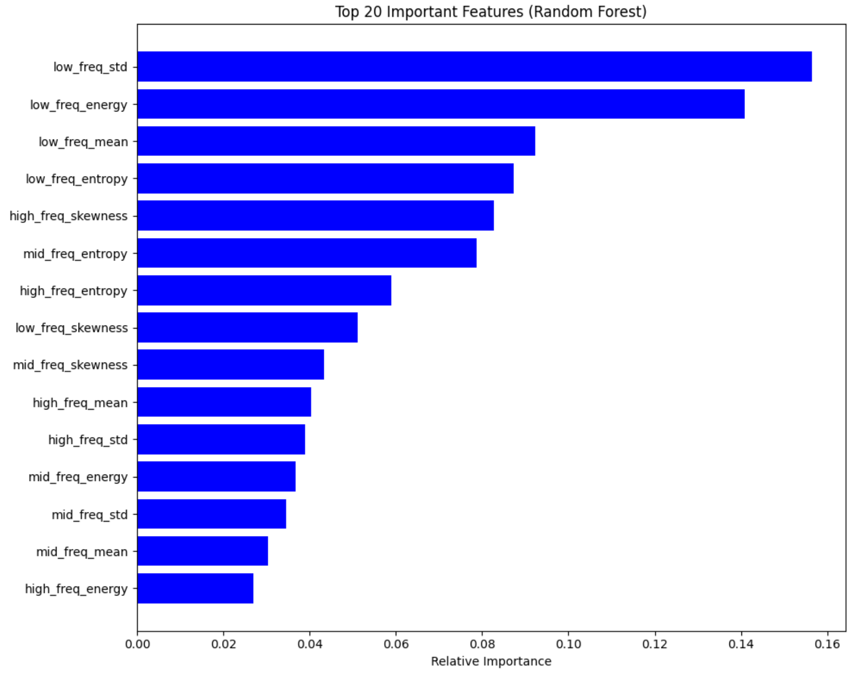

Figure 3.7: Top20 features of RF.

```
Training Random Forest...

Random Forest Results:
Accuracy: 0.885
AUC: 0.885

Classification Report:
              precision    recall  f1-score   support

           0       0.86      0.93      0.89       200
           1       0.92      0.84      0.88       200

    accuracy                           0.89       400
   macro avg       0.89      0.89      0.88       400
weighted avg       0.89      0.89      0.88       400


Training Neural Network...

Neural Network Results:
Accuracy: 0.833
AUC: 0.833

Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.86      0.84       200
           1       0.85      0.81      0.83       200

    accuracy                           0.83       400
   macro avg       0.83      0.83      0.83       400
weighted avg       0.83      0.83      0.83       400
```

Figure 3.9: Classification report

3.4.3 Classification utilizing all features

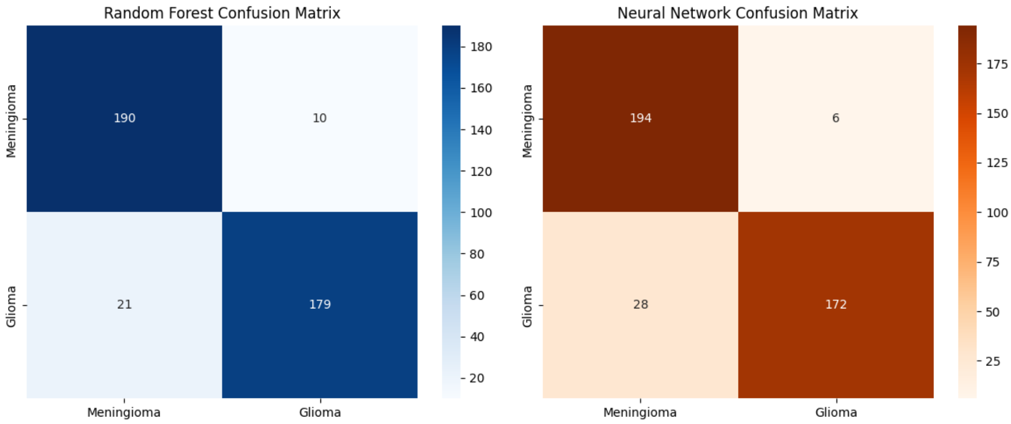

Figure 3.10: Metric results.

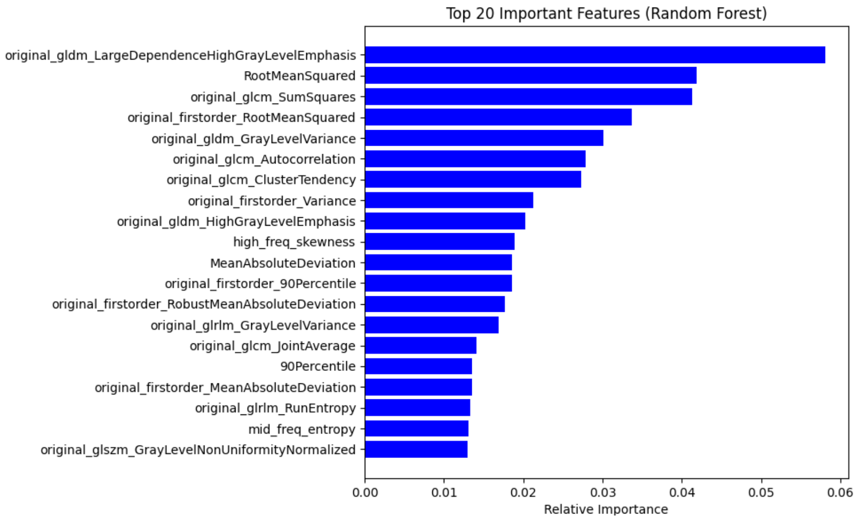

Figure 3.11: Top20 features of RF.

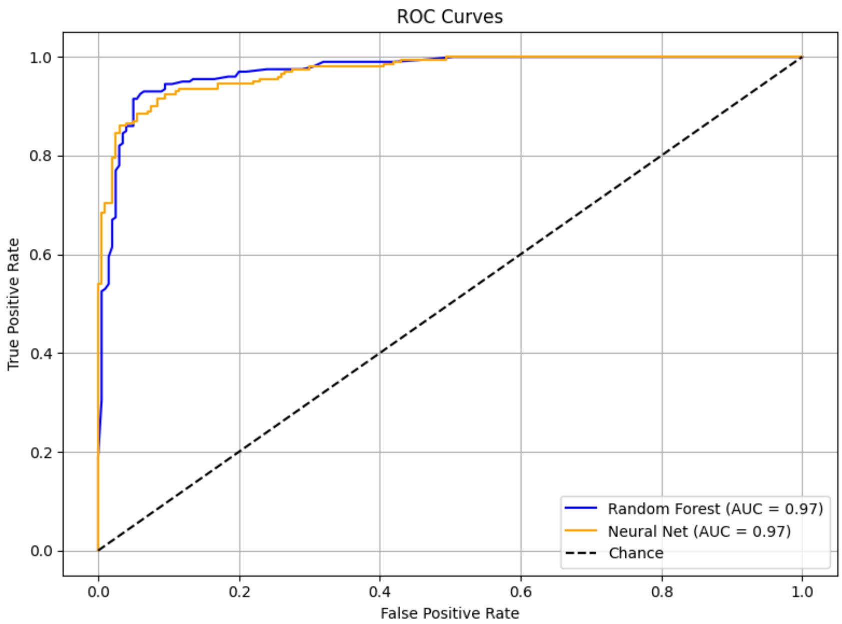

Figure 3.12: RoC curves for RF and MLP-nn.

```
Training Random Forest...

Random Forest Results:
Accuracy: 0.922
AUC: 0.922

Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.95      0.92       200
           1       0.95      0.90      0.92       200

    accuracy                           0.92       400
   macro avg       0.92      0.92      0.92       400
weighted avg       0.92      0.92      0.92       400


Training Neural Network...

Neural Network Results:
Accuracy: 0.915
AUC: 0.915

Classification Report:
              precision    recall  f1-score   support

           0       0.87      0.97      0.92       200
           1       0.97      0.86      0.91       200

    accuracy                           0.92       400
   macro avg       0.92      0.92      0.91       400
weighted avg       0.92      0.92      0.91       400
```

Figure 3.13: Classification report

Chapter 4

Conclusion

Bibliography

[1] https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset Accessed: 2025-05-09.