

# Brain Tumor Classification

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# Problem Statement

- Manual interpretation
  - time-consuming
  - prone to errors

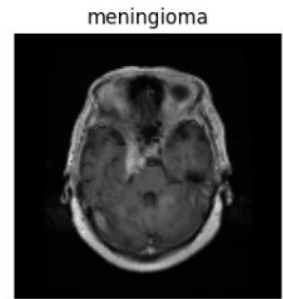
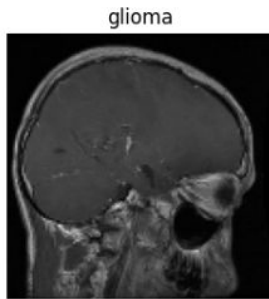
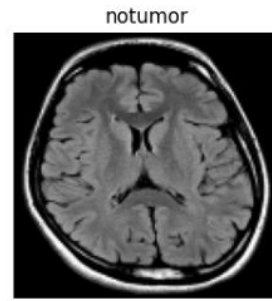
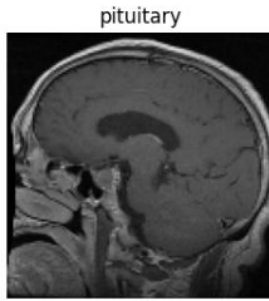


- Increasing number of MRI scans → **Automated solution**

**Develop a deep learning-based model that can automatically classify brain tumors into multiple categories to assist in the early detection, diagnosis, and treatment planning for patients**

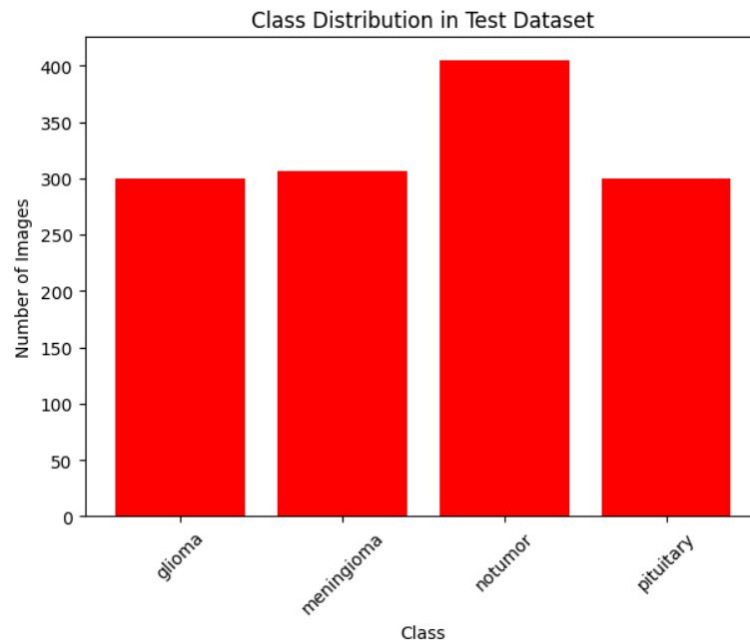
# Dataset

- Dataset : 7023 human brain MRI images
  - Training dataset: 5712 images
  - Testing dataset: 1311 images
- 4 classes :
  - Glioma
  - Meningioma
  - Pituitary
  - No tumor



# Exploratory Data Analysis

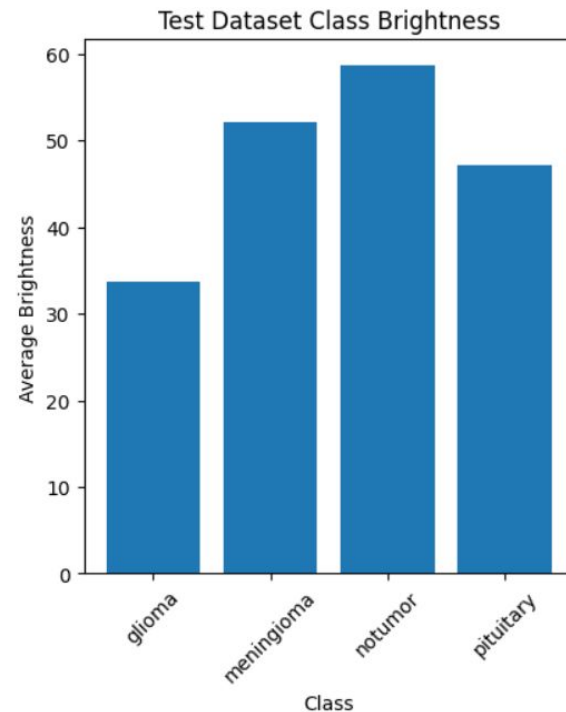
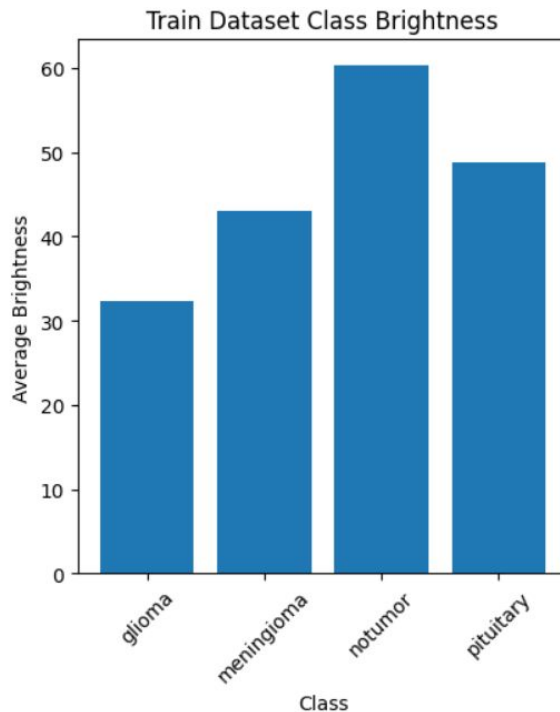
## Class distribution



# Exploratory Data Analysis

## Image brightness

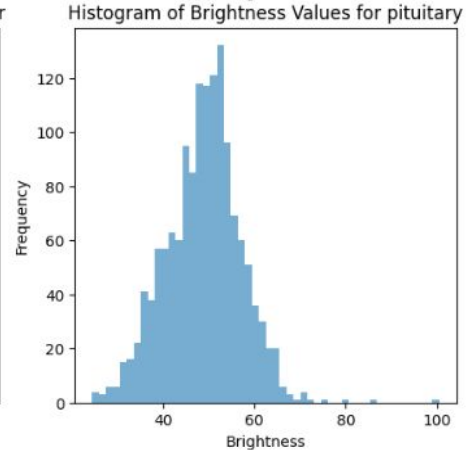
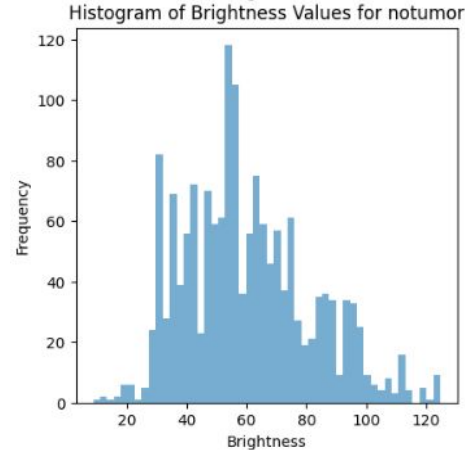
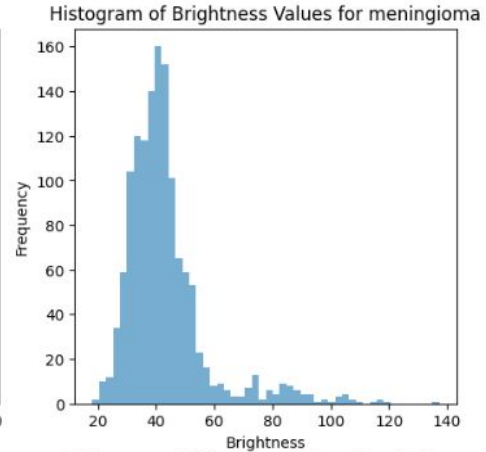
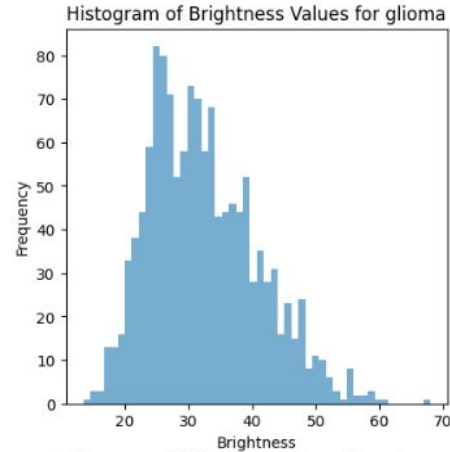
Images in the glioma class are darker than the other classes



# Exploratory Data Analysis

## Histogram of brightness

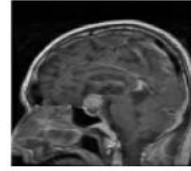
Poor contrast for the Meningioma and pituitary classes



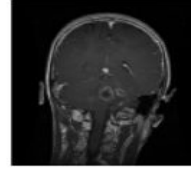
# Preprocessing

- One hot encoding labels
- Filter images : 5x5 Gaussian filter to reduce noise
- Cropping images: focus on the brain area
- Adjusting contrast: enhance the image quality
- Normalize image to [0,1]
- Resizing images to 150x150

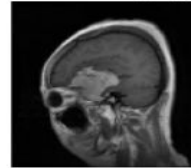
Before Cropping



Before Cropping



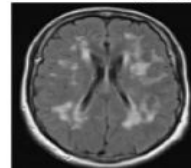
Before Cropping



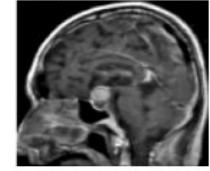
Before Cropping



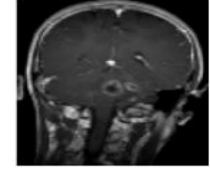
Before Cropping



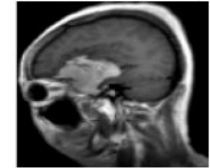
After Cropping and adjusting contrast



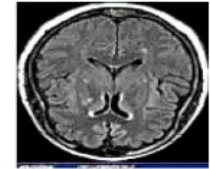
After Cropping and adjusting contrast



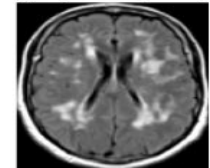
After Cropping and adjusting contrast



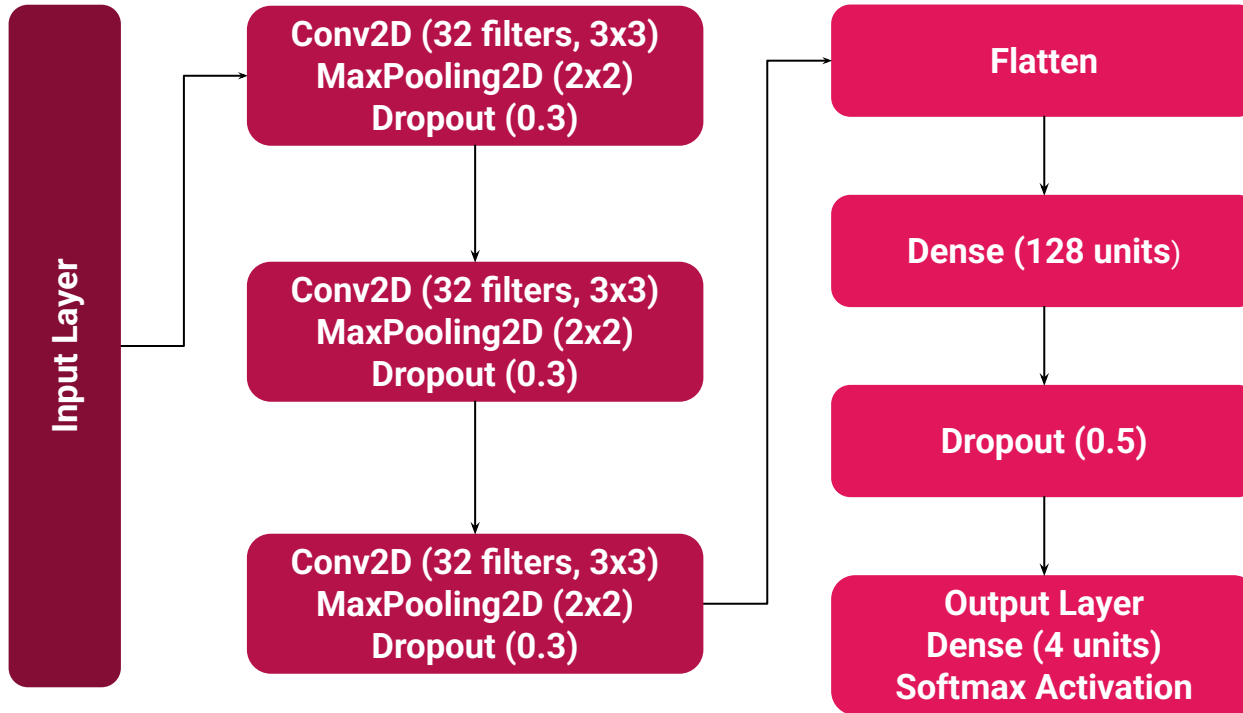
After Cropping and adjusting contrast



After Cropping and adjusting contrast

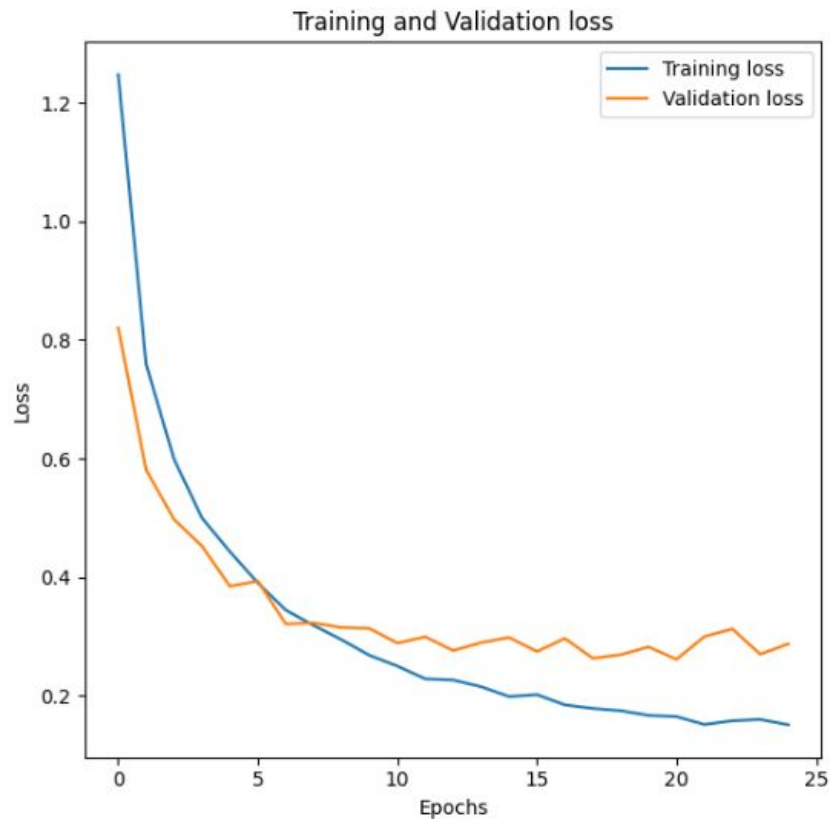
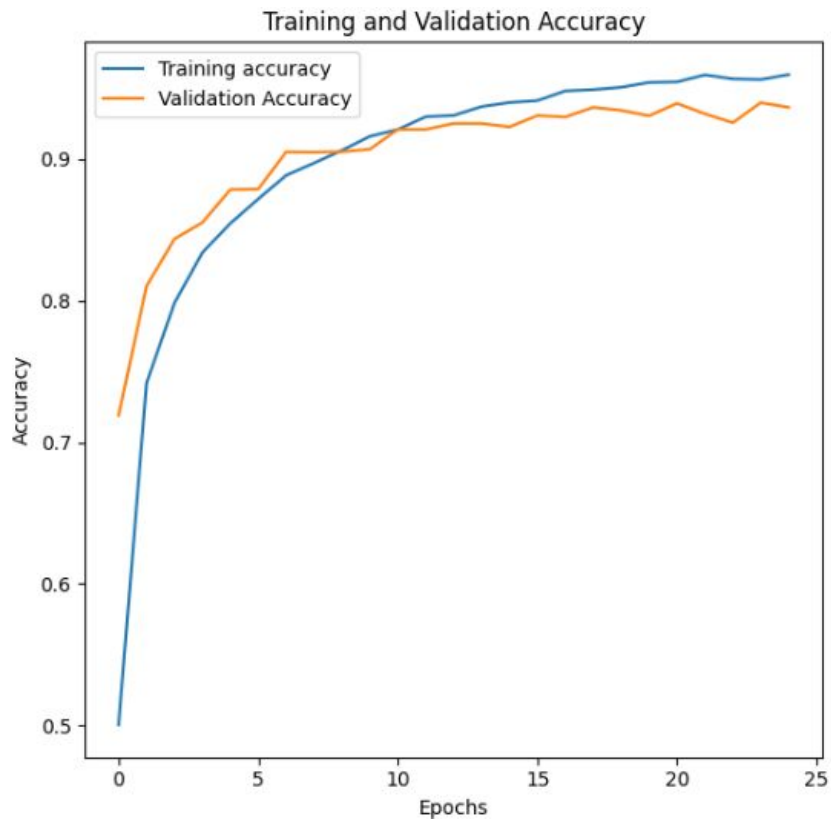


# Modeling





# Modeling



# Evaluation

- The test set was preprocessed similarly to the training set
- Results

Test Loss: 0.2509309947490692

Test Accuracy: 0.9320312738418579

# Hyperparameter tuning

The tuned parameters are:

- The number of filters in the 3 convolutional blocks
- The dimensionality of the output space in the dense layer
- The learning rate of the optimizer “adam”

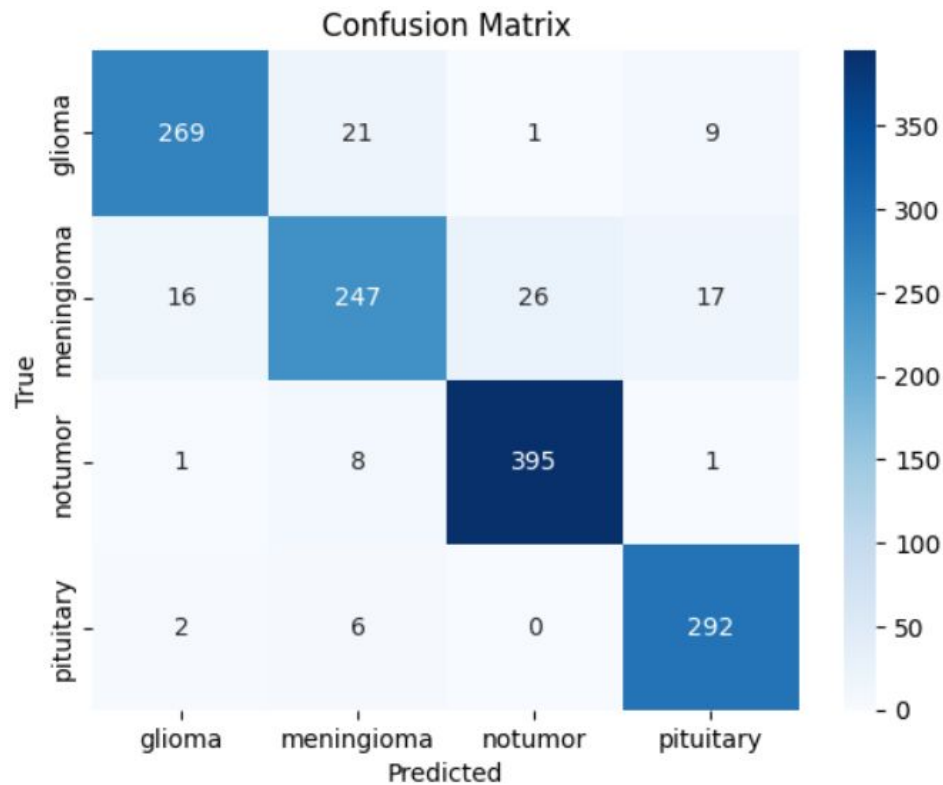
The best parameters are:

- 'filters\_1': 64, 'filters\_2': 64, 'filters\_3': 512,
- 'dense\_units': 192,
- 'learning\_rate': 0.000675

Mean validation accuracy cross folds	Standard deviation of validation accuracy across folds
0.96	0.024

# Evaluation of the best model

Metric	Value
Precision	0.915
Recall	0.913
F1 score	0.913
AUC-ROC	0.985



# Conclusion

- Objective: classify brain Tumor MRI into 4 classes
- Trained CNN model:
  - 3 convolutional blocks with progressively increasing filter sizes and depths containing
    - Convolutional layer,
    - A max pooling layers to reduce spatial dimensions and retain important features.
    - A dropout layers to help mitigate overfitting
  - A layer to flatten the features into a one-dimensional vector
  - A dense layer with ReLU activation.
  - A softmax output layer is used for classification
- Results after tuning
  - High accuracy rate of 91%.
  - High recall rate 91%

# Future work

- Generate more data: use data augmentation techniques (Rotating, shifting, flipping, Shearing, etc)
- Increase model complexity: adding more layers or more neurons in the dense layers.
- Tune more hyperparameters (batch size, dropout rate, etc)

Thank You!