BRAIN TUMOR CLASSIFICATION USING DEEP LEARNING

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ABSTRACT

Brain tumors are aggressive, affecting 84,000 people and causing 18,600 deaths in 2021. MRI is the most effective detection method. Brain tumors cause severe physical, cognitive, and psychological impacts. Faster diagnosis and treatment are vital. Neural networks offer high accuracy in brain tumor image classification tasks.

This project compares deep learning models—CNN, and Transfer Learning—for brain tumor identification and classification. Using 3,264 T1-weighted contrast-enhanced images (cleaned and augmented), it began with binary classification and extended to multi-class classification of Glioma Tumors, Meningioma Tumors, and Pituitary Tumors.

INTRODUCTION

- Brain tumors are challenging to detect non-invasively, and MRI combined with machine learning improves accuracy over manual methods.
- Dataset: Used 3,264 diverse MRI images for robust training.
- Architecture: Used Resnet models for advanced feature extraction and classification.
- Classification: Identified gliomas, meningiomas, pituitary tumors, and healthy tissues using multiple models.
- Analysis: Performance evaluated via metrics, highlighting model accuracy and guiding improvements.

MOTIVATION

Brain tumors are a critical health concern, and early detection is vital for effective treatment. This project utilizes deep learning to create a reliable system for accurate brain tumor classification, assisting medical professionals in making timely diagnoses. By leveraging and enhancing publicly available MRI datasets, it demonstrates the potential of AI in medical diagnostics while encouraging collaboration with healthcare providers for future improvements. The system is designed to be accessible to doctors and patients, fostering better communication and informed, patient-centric care.

PROBLEM

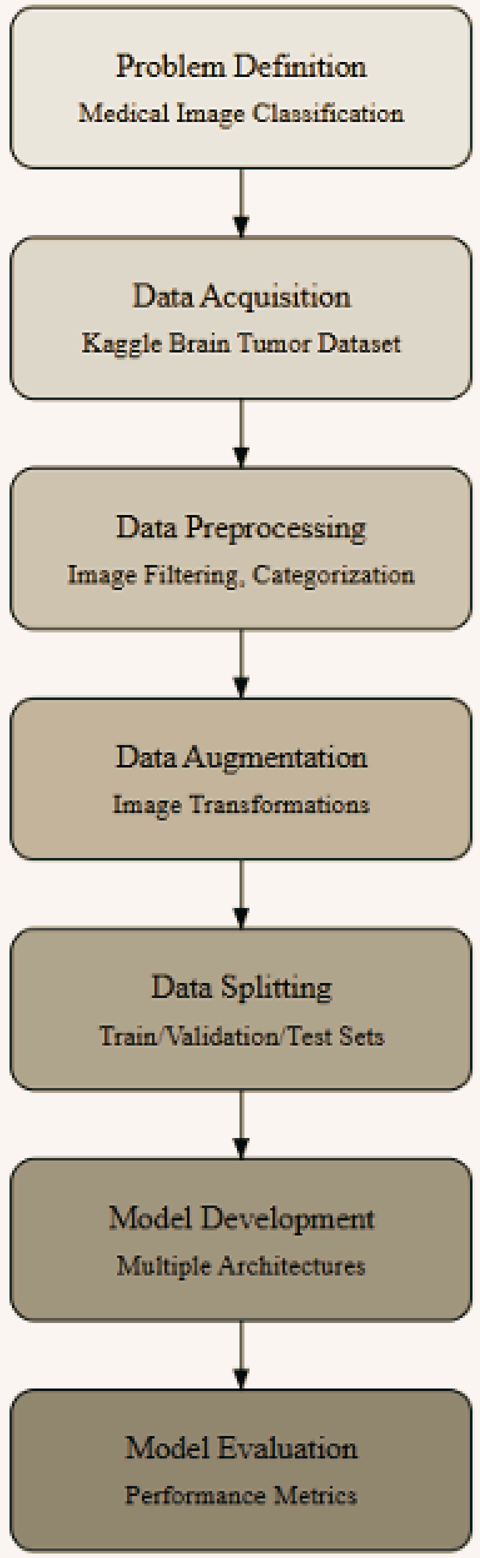
- Brain tumor detection is challenging due to MRI complexity and model limitations. This project compares ResNet-50 and ResNet-101 for classifying glioma, meningioma, pituitary tumors, and healthy brains.

- The study aims to identify the best-performing model to improve accuracy, aiding precise diagnoses and patient outcomes.

OBJECTIVE

The primary goal is to develop an advanced framework for detecting and classifying brain tumors using T1-weighted MRI images, with a focus on accurately identifying tumor types. The project aims to leverage publicly available datasets and cutting-edge methodologies to construct models with superior detection performance. Key efforts are directed at addressing challenges from variations in MRI acquisition, preprocessing, and scanning procedures through data augmentation and domain adaptation techniques. The initiative prioritizes enhancing the accuracy and reliability of brain tumor diagnosis, improving the classification process, and enabling more effective medical interventions for better patient outcomes.

BRAIN TUMOR CLASSIFICATION WORKFLOW



METHODOLOGY

EXPLORATORY DATA ANALYSIS (EDA)

Sample Image Visualization

- Visualized 4 grayscale images per class: Glioma, Meningioma, Normal, Pituitary.
- Observed variations in anatomical structures.

Dataset Distribution

- Visualized class-wise image count using a bar chart.
- Noted slight class imbalance; augmentation identified as a solution.

Dataset Organization

- Images split into Training (80%) and Validation (20%) subsets.
- Organized into class-specific directories for efficient access.

METHODOLOGY

DATA PREPROCESSING

Image Resizing

Standardized all images to 224x224 pixels to meet ResNet input requirements.

Data Augmentation

Techniques used:

- Rotation: ±20°
- Width/Height Shifts: 20%
- Shear Transformation: 20%
- Zoom: 20%
- Horizontal Flip
- Fill Mode: Nearest Neighbor

Normalization

- Applied preprocess_input to scale pixel values to [-1, 1].
- Ensures compatibility with pre-trained ResNet models.

METHODOLOGY

DATASET PREPARATION AND METHODOLOGY OUTCOMES

Dataset Division

- Training Set: 2,296 images (80%) with augmentation pipeline applied.

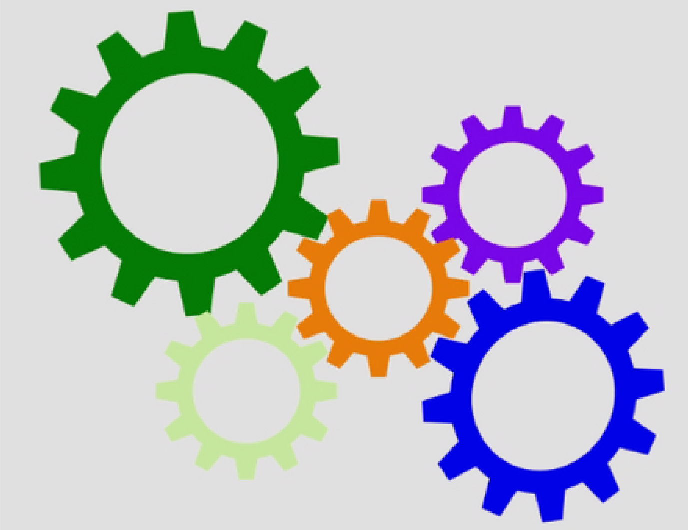
- Validation Set: 574 images (20%) with simple normalization.

Rationale for Split

- Balanced learning and evaluation.
- Prevents underfitting and ensures reliable performance metrics.

Key Outcomes

- Ensured clean, balanced, and standardized input data for model training.
- Augmentation addressed class imbalance and improved generalization.
- Preprocessing pipeline optimized for ResNet-50 and ResNet-101 architectures.



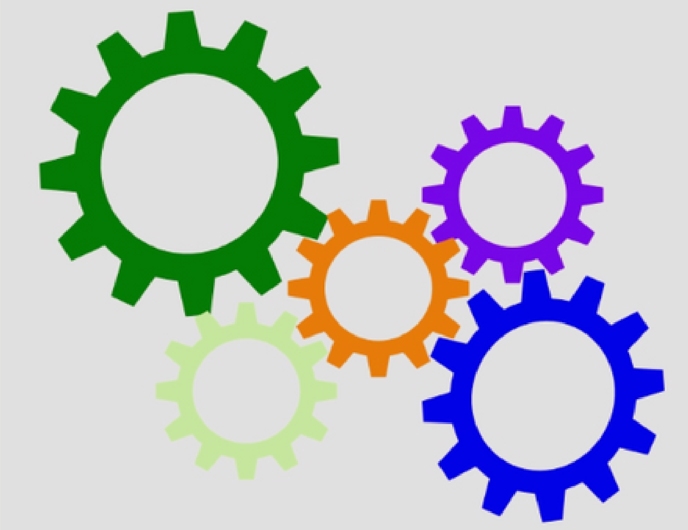
IMPLEMETATION

Dataset Overview:

MRI images were categorized into glioma, meningioma, pituitary tumor, and normal, sourced from Kaggle. Class distribution was analyzed to detect imbalances.

Data Preprocessing:

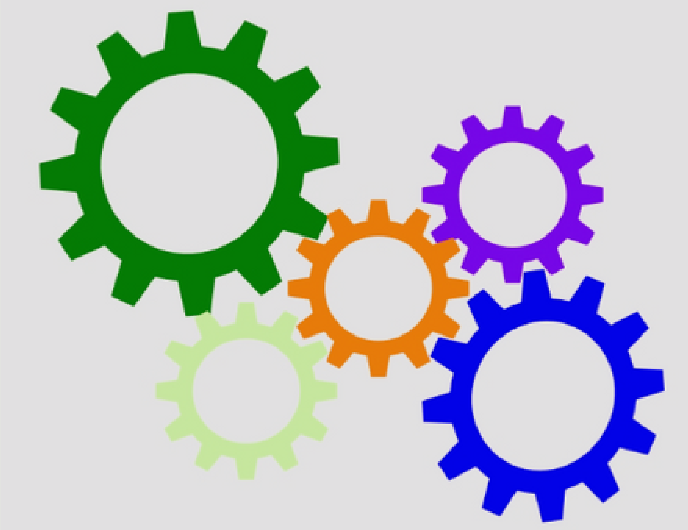
- **Path Retrieval:** Collected image paths in .png, .jpg, and .jpeg formats.
- **Data Split:** 80% for training, 20% for validation, organized into directories.
- **Augmentation:** Applied rotations, zooms, flips using Keras's ImageDataGenerator to reduce overfitting. Validation images were preprocessed for ResNet compatibility.
- **Data Loading:** Resized images to 224x224, loaded in batches for classification.



IMPLEMETATION

Transfer Learning Models:

- **ResNet50 and ResNet101:** Pre-trained ImageNet weights with frozen layers for feature extraction.
- **Output Layer:** Added a dense layer with four units and softmax activation for classification.
- **Compilation:** Used Adam optimizer and categorical_crossentropy for multi-class classification.



IMPLEMETATION

Model Training:

for 15 epochs using augmented data. Validatio

ed

tion:

- **Accuracy/Loss Trends:** Visualized to assess learning patte convergence.
- **Model Evaluation:** Final scores calculated using the evaluate function.

This approach leverages ResNet models with augmentation for efficien tumor classification.

RESULTS

Comparison Between ResNet-50 and ResNet-101

Accuracy and Loss Comparison

- ResNet-101 achieved higher validation accuracy (88.37%) compared to ResNet-50 (88.19%).
- Validation loss for ResNet-101 was lower (0.2882) than ResNet-50 (0.3520).

Convergence

- ResNet-101 converged faster, reaching peak validation accuracy in ~10 epochs, whereas ResNet-50 required ~15 epochs.

RESULTS

Comparison Between ResNet-50 and ResNet-101

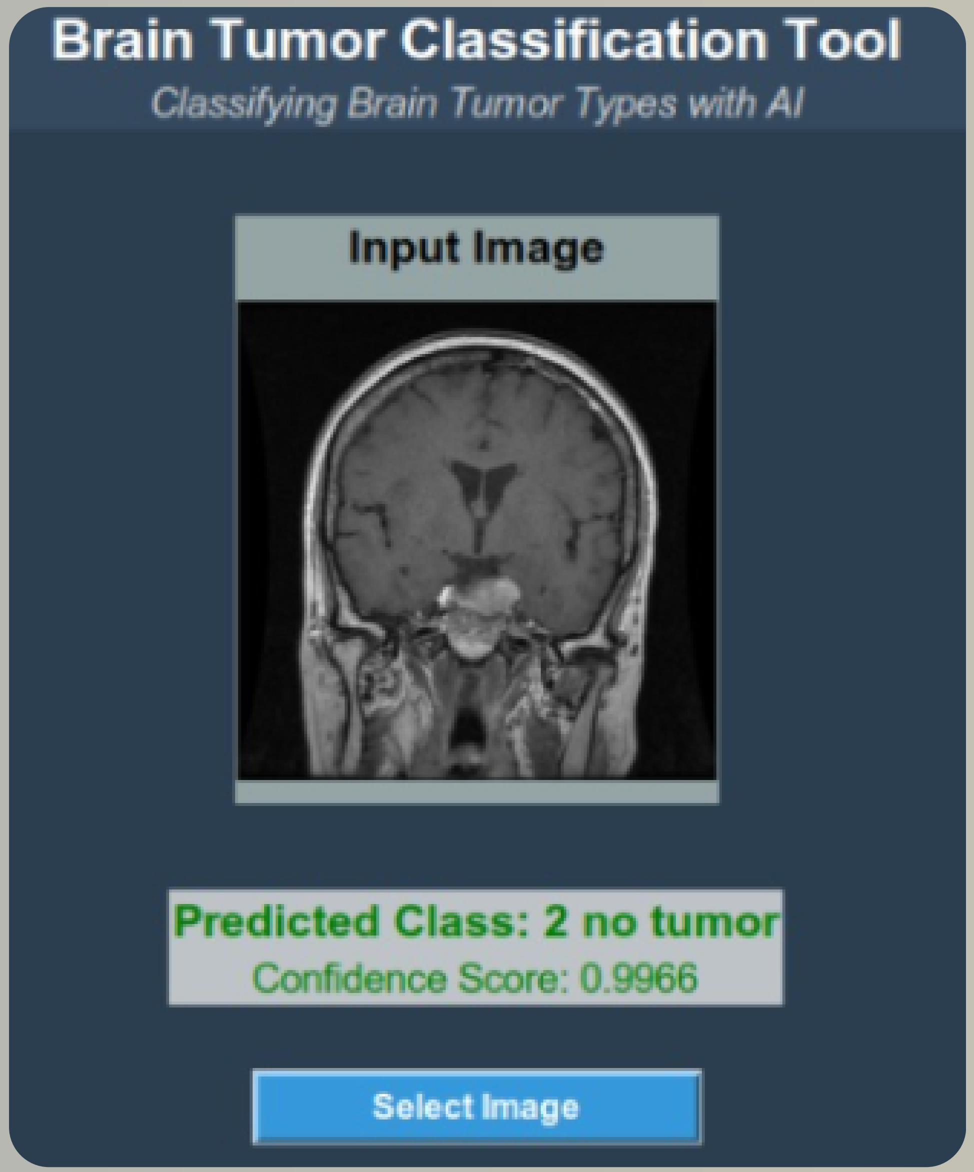
Performance Stability

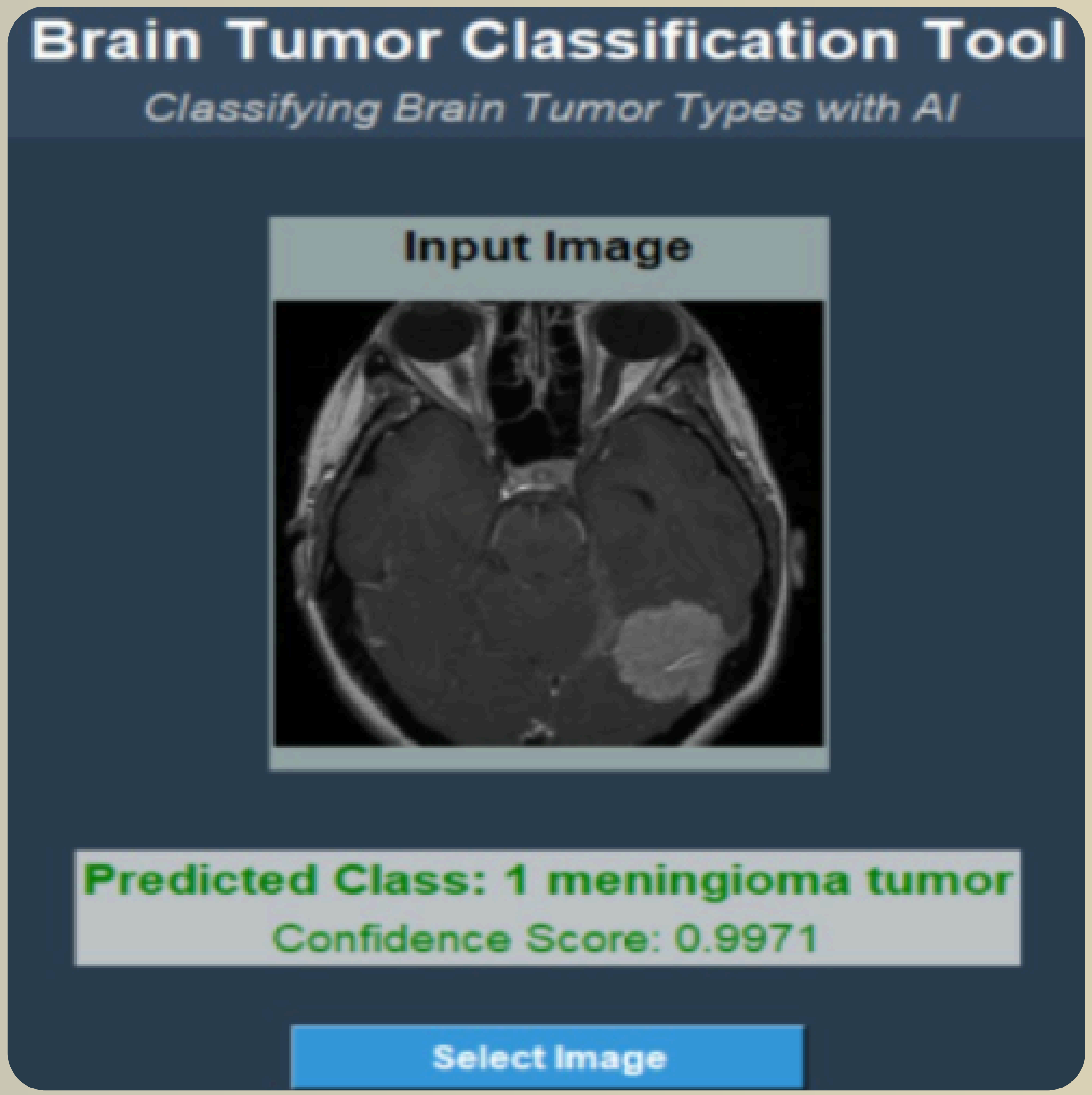
- Accuracy and loss plots demonstrate that ResNet-101 exhibited more stable training and validation performance compared to ResNet-50.

Summary

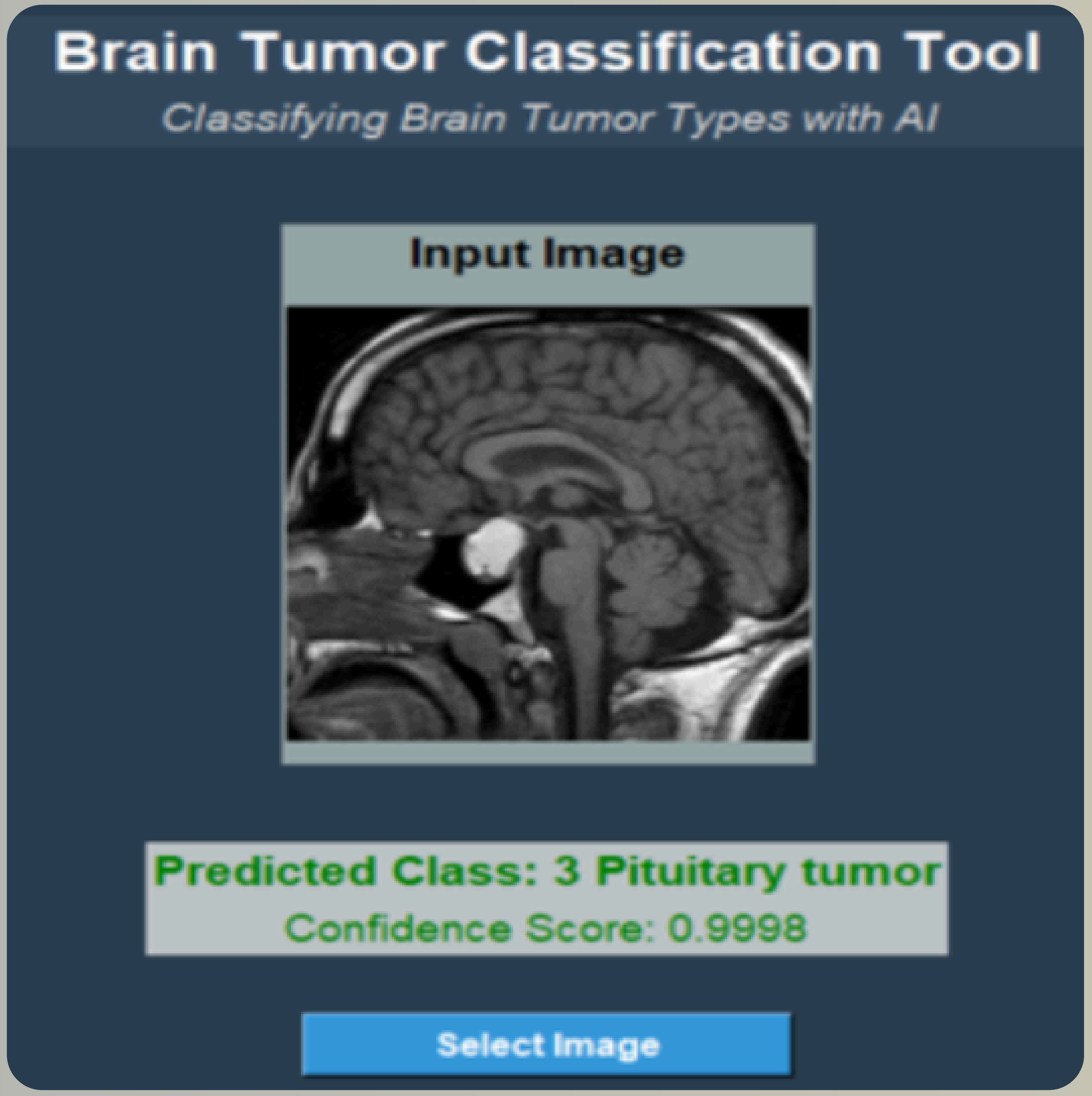
- ResNet-101 outperformed ResNet-50 in both accuracy and loss, showing better generalization due to its deeper architecture, which allowed it to learn more intricate features from MRI scans.

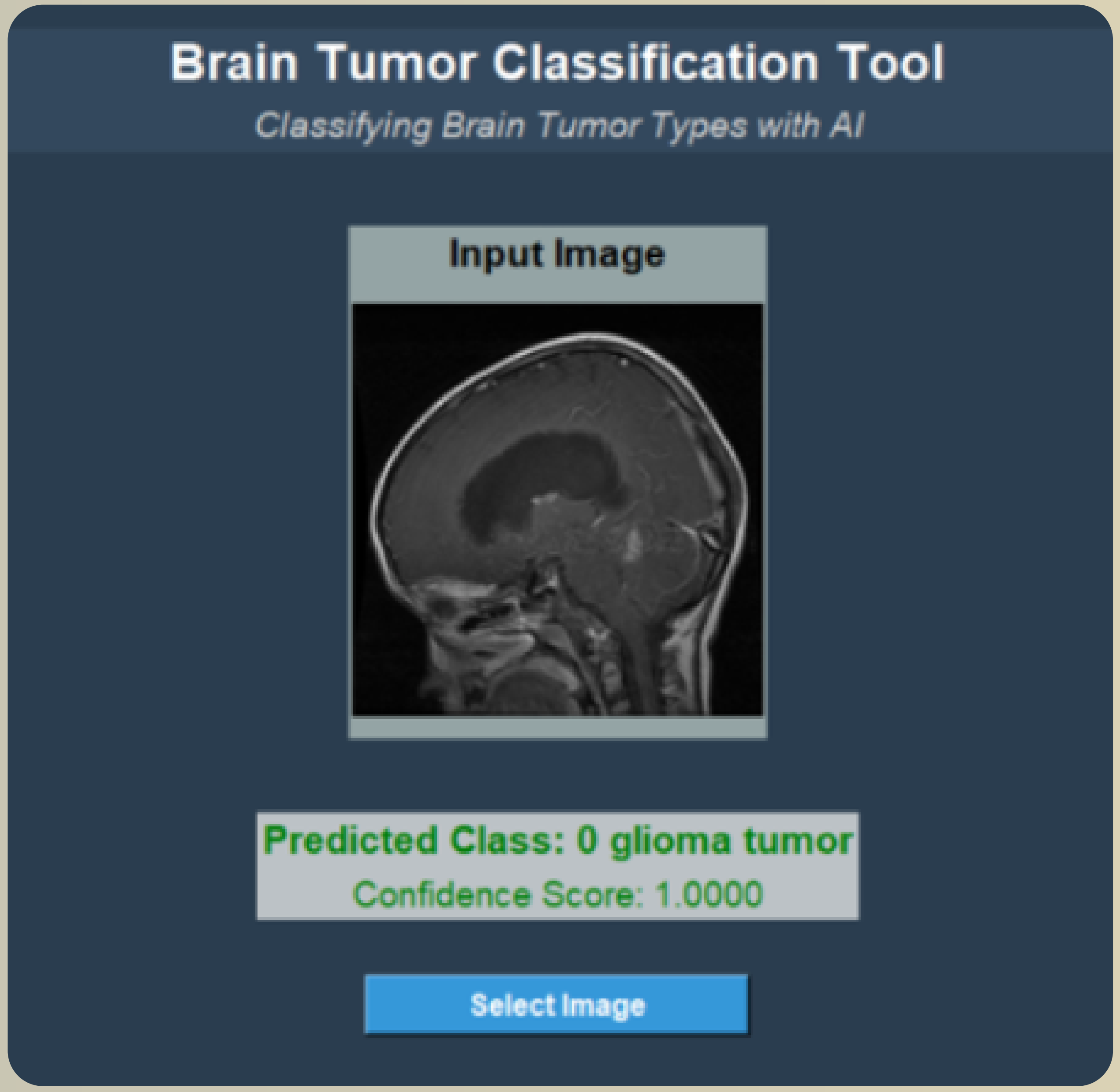
GUI


Brain Tumor Classification Tool
Classifying Brain Tumor Types with AI
Input Image
Predicted Class: 2 no tumor
Confidence Score: 0.9966
Select Image


Brain Tumor Classification Tool
Classifying Brain Tumor Types with AI
Input Image
Predicted Class: 1 meningioma tumor
Confidence Score: 0.9971
Select Image

GUI

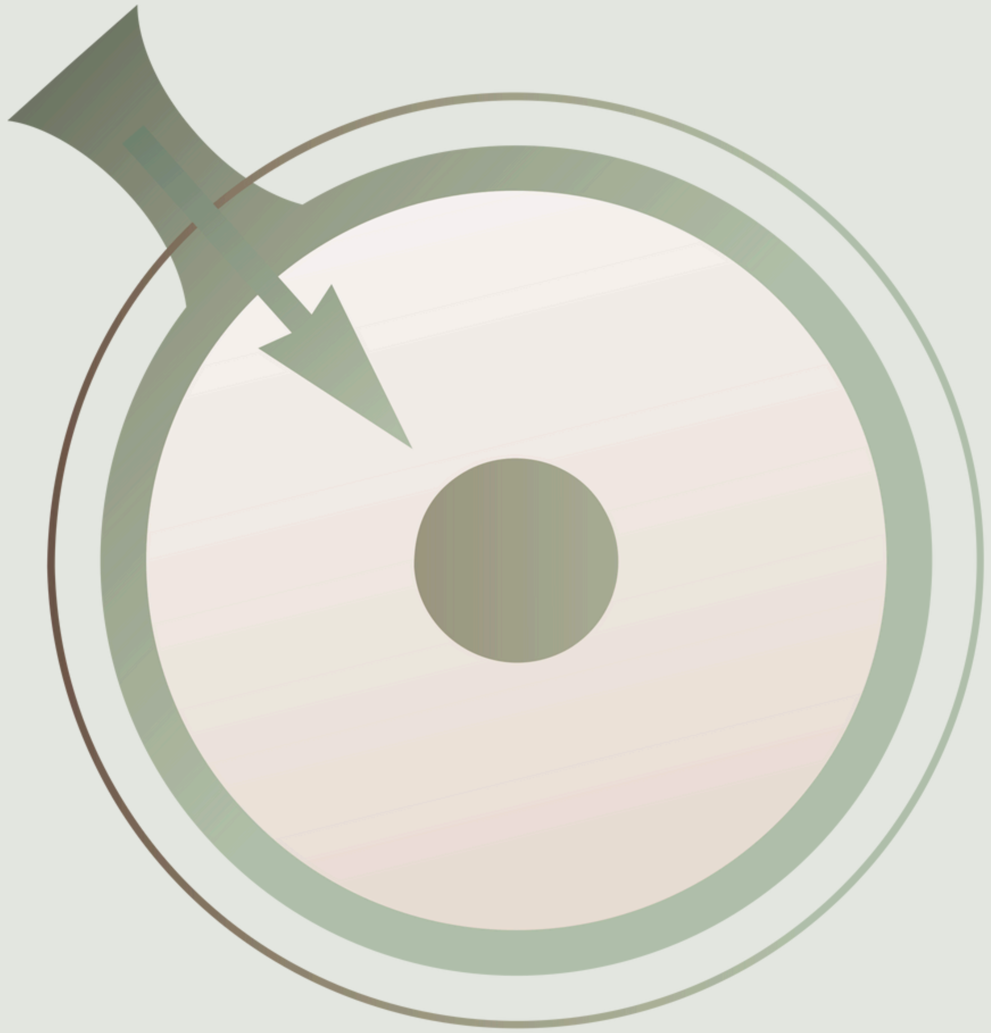

Brain Tumor Classification Tool
Classifying Brain Tumor Types with AI
Input Image
Predicted Class: 3 Pituitary tumor
Confidence Score: 0.9998
Select Image


Brain Tumor Classification Tool
Classifying Brain Tumor Types with AI
Input Image
Predicted Class: 0 glioma tumor
Confidence Score: 1.0000
Select Image

CONCLUSION

The comparison of ResNet-50 and ResNet-101 models for brain tumor classification highlights ResNet-101's superior performance. ResNet-101 achieved higher validation accuracy (88.37% vs. 88.19%), lower validation loss (0.2882 vs. 0.3520), and faster convergence (10 vs. 15 epochs). Its deeper architecture allowed for learning complex features, resulting in better generalization and stability during training.

In conclusion, ResNet-101 is the preferred model for its higher accuracy, efficiency, and reliability in brain tumor classification.



Thank You

For your attention