מטלת גמר בבינה מלאכותית

"האם ניתן לסווג סוג גידול מוחי בעזרת בינה מלאכותית?"

טכנולוגיות דיגיטליות ברפואה - תשפ"ד

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Abstract

Brain tumors pose a significant medical challenge, requiring precise and early diagnosis for effective treatment. Magnetic Resonance Imaging (MRI) serves as a primary tool for tumor identification, but manual analysis is time-consuming and prone to subjectivity. In this study, we propose an AI-based approach to classify brain tumors using deep learning models, named - InceptionV3, AlexNet, and ResNet50. Our dataset comprises 7,023 MRI images categorized into Glioma, Meningioma, Pituitary Adenoma, and No Tumor collected from Kaggle's brain tumor dataset and supplemented with additional medical sources.Preprocessing steps included data augmentation, resizing, and normalization. The results indicate that InceptionV3 outperformed other models, achieving an accuracy of 81.5%. The findings highlight the potential of deep learning in brain tumor diagnosis and suggest pathways for future improvements.

Introduction

Brain tumor classification is a critical challenge in medical diagnostics, as manual MRI analysis is both time-consuming and prone to subjective interpretation errors. AI-driven deep learning models provide a promising solution by offering automated, accurate, and efficient tumor detection. This project aims to classify brain tumors into Glioma, Meningioma, and Pituitary Adenoma using deep learning architectures. We explore various convolutional neural networks (CNNs), such as InceptionV3, AlexNet, and ResNet50, to determine the most effective model for this task.

Past Work and Project Uniqueness

Past Work

Previous studies have focused on binary classification of tumors or single-model approaches, focusing on different methodologies:

- **Segmentation and Grading**: Naser & Deen (2020) developed a segmentation and grading approach specifically for gliomas [11]. Similarly, Isin et al. (2016) reviewed segmentation techniques and their application in deep learning-based medical imaging [8].
- **Binary Classification**: Studies such as Khairandish et al. (2022) concentrated on distinguishing between benign and malignant tumors rather than performing multi-class classification [9]. Mohsen et al. (2018) classified tumors into broad categories like normal, glioblastoma, sarcoma, and metastatic carcinoma, but lacked granularity [6].
- **Deep Learning Applications**: Musallam et al. (2022) implemented a CNN-based model for tumor classification [5], while Amin et al. (2018) applied a deep convolutional approach to detect brain tumors using big data analysis [10].

- **AI Explainability**: Zeineldin et al. (2022) introduced an explainable AI framework for MRI analysis, which improved model interpretability but did not fully integrate advanced CNN architectures [4].

Project Uniqueness

Unlike previous studies, our project introduces several key innovations:

- **Multi-Class Classification**: Most prior research has focused on binary classification (tumor vs. no tumor), whereas our study provides a detailed classification of tumor subtypes, including Glioma, Meningioma, and Pituitary Adenoma [2,6].
- **Enhanced Generalization**: Many previous studies trained their models on a single dataset [1,3], whereas our model was trained using a consolidated dataset from three different sources, making it more robust and generalizable.
- **Integration of Multiple CNN Models**: Previous works often used a single CNN architecture (e.g., ResNet or AlexNet) [5,11], while our study integrates InceptionV3, AlexNet, and ResNet50, leveraging the strengths of each model for a comprehensive performance comparison.
- **Explainability Features**: We incorporated Grad-CAM visualization to highlight model decision-making, which improves the interpretability of the AI system and increases its potential for medical use [4,8].

Materials and Methods

Dataset and Brain Tumor Types

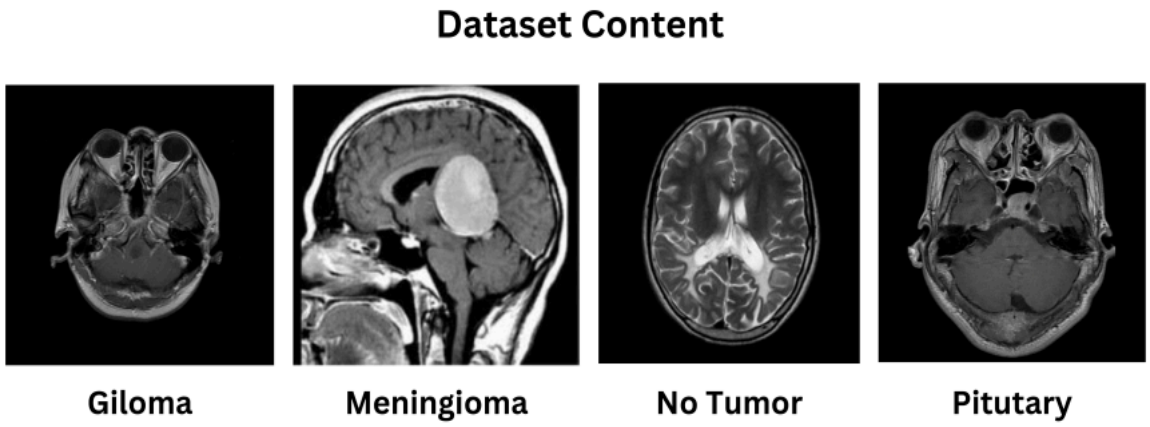
The dataset used in this study was obtained from Kaggle's brain tumor dataset, combined with additional medical sources. It consists of 7,023 MRI images, representing**:**

Brain Tumor Types:

- **Glioma:** Gliomas are tumors that develop from glial cells, which support and protect neurons in the brain. They make up about 30% of all brain tumors and account for 80% of all malignant tumors. Symptoms include severe headaches, seizures, cognitive impairment, and motor dysfunction. Gliomas are highly aggressive, and early detection is critical for improving patient outcomes.
- **Meningioma:** Meningiomas originate from the meninges, the protective layers surrounding the brain and spinal cord. They are the most common type of benign brain tumors, comprising 37% of all primary brain tumors. Meningiomas are more prevalent in women and can cause headaches, visual disturbances, and pressure on adjacent brain structures. While usually slow growing, some can become aggressive and require surgical intervention.
- **Pituitary Adenoma:** These tumors develop in the pituitary gland, which regulates essential hormones in the body. Pituitary adenomas constitute 10-15% of all intracranial tumors and are equally common in men and women. They often present in patients aged 30-50 years and can

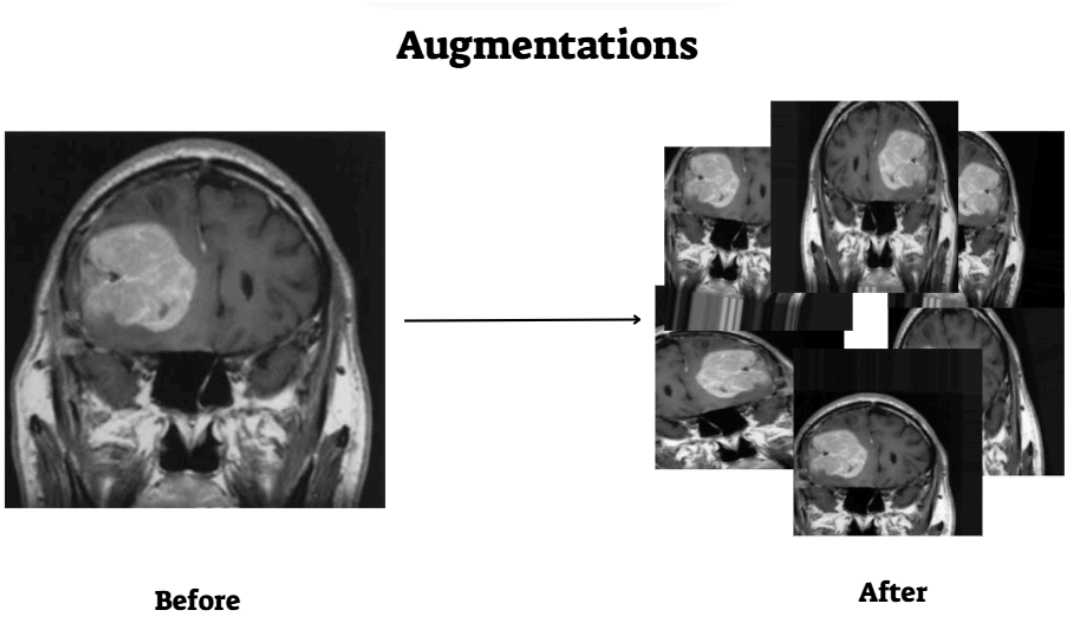
lead to hormonal imbalances, abnormal growth, metabolic issues, and vision problems due to their proximity to the optic nerves.

- **No Tumor (Control Group):** This category includes MRI scans of healthy brain structures, serving as a reference to differentiate abnormal tumor formations from normal anatomy.



Preprocessing:

- **Resizing** images to 224×224 pixels.
- **Data augmentation** (rotation, flipping, brightness adjustments) to enhance model robustness.
- **Normalization** for consistent intensity distribution.
- **Splitting the dataset** into training, validation, and test sets.



Deep Learning Models

Model Setup, Optimization and Comparison

What is CNN?

A Convolutional Neural Network (CNN) is a type of deep learning model designed specifically for image recognition and classification tasks. CNNs apply convolutional filters to extract spatial features such as edges, textures, and complex patterns, making them ideal for medical image analysis.

The main components of a CNN include:

- **Convolutional Layers**: Extract local features from images.
- **Activation Functions (ReLU)**: Introduce non-linearity to the model.
- **Pooling Layers**: Reduce the spatial size of feature maps, improving computational efficiency.
- **Fully Connected Layers**: Map extracted features to classification labels.

Optimization and Hyperparameter Selection

All models were optimized using the Adam optimizer, which adjusts learning rates dynamically to accelerate convergence and avoid local minimum. The optimal hyperparameters for each model were fine-tuned through experimentation, ensuring the best possible performance.

These parameters included:

- **Batch size**: Number of images processed simultaneously during training.
- **Learning rate**: Controls step size updates in the optimizer.
- **Dropout rate**: Reduces overfitting by randomly deactivating neurons.
- **Epochs**: Number of full passes through the datasets

Inception V3 - Architecture, Features, Hyperparameters & Evaluation.

InceptionV3 is a deep convolutional neural network (CNN) that employs Inception modules, which apply multiple kernel sizes (1x1, 3x3, 5x5, and 7x7 filters) within the same convolutional layer. This allows the model to extract hierarchical features at different spatial scales, capturing fine details and larger structures in MRI images simultaneously.

The architecture is composed of:

- Stem convolutional layers: Extracts fundamental low-level features (edges, corners, textures).

- Multiple stacked Inception modules: Performs multi-scale feature extraction, allowing the model to capture both small and large details within brain tumor images.
- Auxiliary classifiers: Intermediate classifiers added to prevent vanishing gradients and guide early layers towards meaningful feature extraction.
- Fully connected layers & Softmax activation: Converts extracted features into classification scores.

Advantages:

- Multi-scale feature extraction allows the model to analyze brain tumor images with various structural patterns.
- Efficient computation: The model uses factorized convolutions and dimensionality reduction techniques to speed up processing without losing accuracy.
- Better generalization: Due to deep hierarchical feature learning, InceptionV3 is capable of recognizing diverse tumor shapes and structures.
- Works well with medical imaging: Given its ability to handle fine-grained details, it is particularly useful for MRI scans where tumors have complex and varied textures.

Key features of the Inception V3 architecture:

Multi-Scale Feature Extraction:

- The Inception module combines different filter sizes (1x1, 3x3, 5x5, and 7x7) in a parallel fashion to extract local and global patterns simultaneously.

Factorized Convolutions for Efficiency:

- Reduces computational cost by breaking down large convolutions into multiple smaller convolutions.Example: A **5x5 convolution** is replaced by **two 3x3 convolutions**, reducing the number of parameters while maintaining feature richness.

Batch Normalization:

- Applied across multiple layers to **stabilize training**, speed up convergence, and improve performance.

Auxiliary Classifiers:

- Added at **intermediate layers** to act as **early predictors**, ensuring gradients propagate effectively and preventing **vanishing gradients** in deep networks.

Asymmetric Convolutions:

- **Replaces larger kernels (e.g., 7x7) with a sequence of smaller convolutions (1x7 followed by 7x1)**, enhancing computational efficiency while preserving spatial awareness.

Efficient Grid Reduction:

- **1x1 convolutions** and **stride convolutions** are used to reduce feature map dimensions, significantly **lowering computational complexity**.

Optimal Hyperparameters

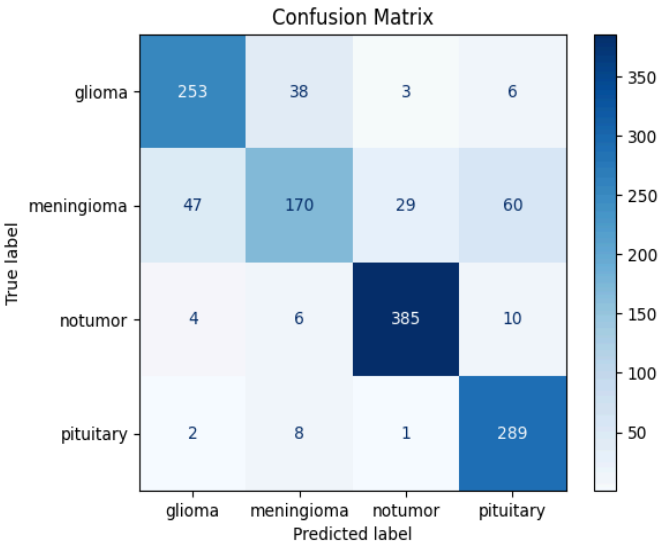
To achieve the best performance, the following hyperparameters were used:

Hyperparameter	***Value***	***Purpose***
Learning Rate	0.0001	Prevents large weight updates, ensuring stable convergence.
Batch Size	32	Maintains a balance between computation time and training stability.
Dropout	0.5	Reduces overfitting by randomly deactivating neurons during training.
Number Of Epochs	25	Ensures sufficient training without excessive overfitting.
Optimizer	Adam	Adaptive optimizer for efficient weight updates.
Loss Function	Categorical Crossentropy	Handles multi-class tumor classification effectively.

Performance Evaluation

Metric	***Performance***
Accuracy	81.5%
Precision	0.82
Recall (Sensitivity)	0.81
F1 - Score	0.81

Confusion Matrix	Best results in distinguishing **Glioma, Meningioma, and Pituitary Tumors.**



InceptionV3 Confusion Matrix

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Weighted F1 Score: 0.8293
Classification Report:
              precision    recall  f1-score   support

      glioma       0.83      0.84      0.83       300
  meningioma       0.77      0.56      0.64       306
     notumor       0.92      0.95      0.94       405
   pituitary       0.79      0.96      0.87       300

    accuracy                           0.84      1311
   macro avg       0.83      0.83      0.82      1311
weighted avg       0.83      0.84      0.83      1311
```

InceptionV3 F1 Score Table

AlexNet - Architecture, Features, Hyperparameters & Evaluation.

Architecture & Design

AlexNet is a **deep convolutional neural network (CNN) model** designed for **high-speed and efficient image classification**. It consists of **five convolutional layers followed by three fully connected layers**, making it **deeper than traditional CNNs but shallower than InceptionV3 and ResNet50**.

Advantages:

- **Lightweight and computationally efficient** – Suitable for **low-resource environments and fast classification**.
- **Faster training compared to deeper models** like ResNet50 and InceptionV3.
- **Performs well on simple classification tasks**, distinguishing between **tumor and non-tumor cases** with ease.

- **Uses fewer parameters** than ResNet50, **reducing memory requirements** while maintaining accuracy.
- **Effective feature extraction in medical imaging** for **MRI-based tumor detection**.

Architecture Breakdown:

Input Layer: Accepts **RGB images** of size *(img_height, img_width, 3)*.

Convolutional Layers (Conv1 – Conv5):

- Extract **hierarchical features** using filters of varying sizes.
- Uses **ReLU activation** for non-linearity.
- **MaxPooling layers** (after Conv1, Conv2, and Conv5) reduce dimensions.

Fully Connected Layers (FC6 – FC7):

- **Two dense layers with 4096 neurons each**, activated with ReLU.
- **Dropout (0.5)** applied to prevent overfitting.

Output Layer:

- A **Softmax classifier** with **4 output neurons** for multi-class classification.

Key features of the AlexNet architecture:

ReLU Activation (Rectified Linear Units):

- Introduced non-linearity for faster training and improved performance.

Overlapping Max Pooling:

- Reduces feature map size while preserving spatial features, leading to better translation invariance.

Local Response Normalization (LRN):

- Helps mitigate vanishing gradients, normalizes activations, and improves generalization.

Dropout Layers:

- Prevents **overfitting** by randomly deactivating neurons during training.

High-Speed Processing:

- Originally designed for **GPU acceleration**, making it **computationally efficient**.

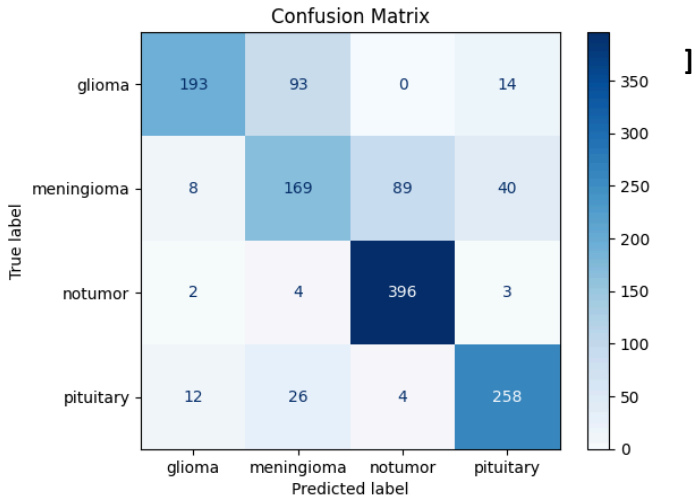
Optimal Hyperparameters

To achieve the best performance, the following hyperparameters were used:

Hyperparameter	***Value***	***Purpose***
Learning Rate	0.0001	Prevents large weight updates, ensuring stable convergence.
Batch Size	64	Improves training efficiency by processing multiple images at once.
Dropout	0.5	Reduces overfitting by randomly deactivating neurons during training.
Number Of Epochs	25	Ensures sufficient training without excessive overfitting.
Optimizer	Adam	Adaptive optimizer for efficient weight updates.
Loss Function	Categorical Crossentropy	Handles multi-class tumor classification effectively.

Performance Evaluation

Metric	***Performance***
Accuracy	*76%*
Precision	0.78
Recall (Sensitivity)	0.74
F1 - Score	0.76
Confusion Matrix	Best results in distinguishing **Glioma, Meningioma, and Pituitary Tumors.**



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Classification Report:

	precision	recall	f1-score	support
glioma	0.90	0.64	0.75	300
meningioma	0.58	0.55	0.57	306
notumor	0.81	0.98	0.89	405
pituitary	0.82	0.86	0.84	300
accuracy			0.77	1311
macro avg	0.78	0.76	0.76	1311
weighted avg	0.78	0.77	0.77	1311

AlexNet Confusion Matrix

AlexNet F1 Score Table

ResNet50 - Architecture, Features, Hyperparameters & Evaluation.

Architecture & Design

ResNet50 (Residual Network with 50 layers) is a deep convolutional neural network (CNN) designed to overcome the vanishing gradient problem in deep networks by introducing residual connections (skip connections). Instead of learning the entire transformation, ResNet50 learns the residual mapping, making deep networks easier to train and optimize for medical image classification tasks.

The ResNet50's architecture composed of:

- **Residual Learning Framework**: Uses skip connections to allow gradient flow through deep layers, preventing the vanishing gradient problem in very deep architectures.
- **Bottleneck Layers**: Instead of using standard convolutional layers, ResNet50 stacks 1x1, 3x3, and 1x1 convolutions to reduce the number of parameters while maintaining deep feature extraction.
- **Batch Normalization**: Applied after each convolutional layer to improve gradient flow, stabilize training, and speed up convergence.
- **Global Average Pooling (GAP)**: Instead of a fully connected layer, GAP reduces overfitting by averaging feature maps before classification.
- **Deep Hierarchical Feature Extraction**: Allows the model to capture both low-level (edges, textures) and high-level (tumor structures, abnormalities) features.

Architectural Breakdown:

- **Input Layer:** 224 × 224 × 3 MRI brain scan images.
- **Conv1 (Initial Convolutional Block):**
- **7x7 Convolution + BatchNorm + ReLU Activation** (Extracts basic features)
- **MaxPooling layer** (3x3, stride 2)
- **Conv2_x Block** (Residual Block 1 - 3 layers)
- **Conv3_x Block** (Residual Block 2 - 4 layers)
- **Conv4_x Block** (Residual Block 3 - 6 layers)
- **Conv5_x Block** (Residual Block 4 - 3 layers)
- **Global Average Pooling (GAP)**
- **Fully Connected (Dense Layer)**
- **Softmax Activation** (4 Classes: Glioma, Meningioma, Pituitary Adenoma, No Tumor)

Advantages:

- **Deep Feature Learning:** The 50-layer deep architecture enables better representation of complex tumor textures and variations.
- **Skip Connections Prevent Vanishing Gradients:** Ensures smooth backpropagation, making training stable.
- **Generalizes Well to Complex Tumor Patterns:** Ideal for distinguishing subtle tumor differences, such as Glioma vs. Meningioma vs. Pituitary Adenoma.
- **Improved Training Efficiency:** Despite its depth, residual connections allow for faster convergence compared to standard deep networks.
- **Strong Performance in Large Datasets:** Works well when trained on large, diverse MRI datasets.

Key Features of ResNet50 for Brain Tumor Classification

ResNet50 (**Residual Network with 50 layers**) introduces several innovative techniques that **enhance deep learning performance**, particularly for **medical image classification** tasks like **brain tumor classification using MRI scans**.

Deep Residual Learning Framework:

- Uses **skip connections** (residual connections) to solve the vanishing gradient problem, allowing deeper networks to train efficiently.
- Instead of learning an entire transformation, ResNet learns residual **mappings**, **simplifying gradient flow.**

Bottleneck Convolutional Blocks:

- **Three-layer block (1x1, 3x3, 1x1 convolutions)** reduces computational cost while maintaining deep feature extraction.
- The **first 1x1 convolution** reduces dimensionality, the **3x3 convolution extracts features**, and the **final 1x1 convolution restores dimensions**.

Batch Normalization for Stable Training:

- Each convolutional layer is followed by **Batch Normalization (BN)** to:
    - **Prevent internal covariate shift** (ensures stable activations).
    - **Speed up convergence** and **reduce overfitting**.
    - **Improve gradient flow**, making deeper networks trainable.

Global Average Pooling (GAP) Instead of Fully Connected Layers:

- Unlike traditional architectures that use **fully connected (dense) layers**, ResNet50:
    - Uses **Global Average Pooling (GAP)** before the classification layer.
    - **Reduces the number of parameters**, lowering overfitting risk.
    - **Increases generalization** by averaging spatial features.

Hierarchical Feature Learning:

- Captures both **low-level and high-level features** using a **deep hierarchical structure**:
    - **Shallow layers** detect **edges, corners, and simple textures**.
    - **Deeper layers** recognize **tumor structures, abnormalities, and classification patterns**.

Identity & Projection Shortcuts:

- **Identity Shortcut**: When input and output dimensions match, **directly skips layers** without additional computation.
- **Projection Shortcut**: When dimensions differ, use **1x1 convolutions to adjust the feature map size**.

Works Well with Transfer Learning:

- Pre-trained **ResNet50 models (trained on ImageNet or medical datasets)** can be **fine-tuned** for MRI tumor classification.
- **Improves accuracy & reduces training time** by using pre-learned features.

Optimized for Large-Scale Datasets:

- Performs **best on large, high-resolution datasets**, leveraging deep feature extraction capabilities.

Enhanced Model Efficiency:

- Despite its depth, **ResNet50 is computationally efficient** compared to traditional deep CNNs, thanks to **residual learning and bottleneck blocks**.

Optimal Hyperparameters

To optimize the classification performance, the following hyperparameters were used:

Hyperparameter	***Value***	***Purpose***
Learning Rate	32	Ensures training stability while optimizing memory usage.
Batch Size	0.0001	Prevents overfitting and allows smooth convergence
Dropout	0.5	Reduces overfitting by randomly deactivating neurons.
Number of Epochs	25	Prevents excessive overfitting while ensuring stable training.
Optimizer	Adam	Adaptive optimizer for efficient weight updates.
Learning Rate	Categorical Crossentropy	Suitable for multi-class tumor classification.

Performance Evaluation

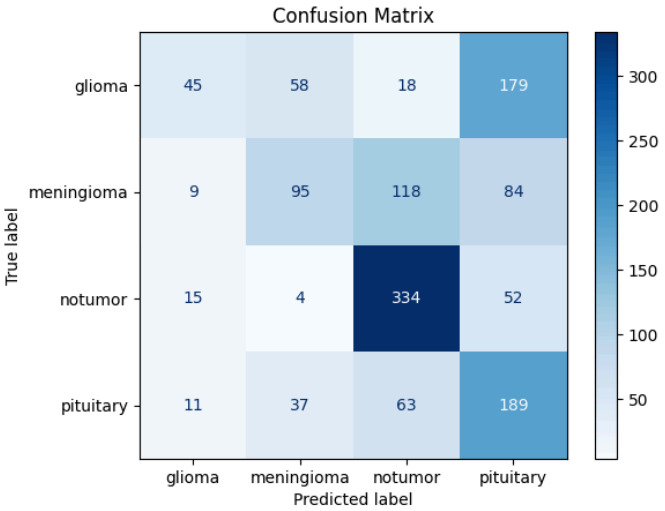
Metric	Performance
Accuracy	*51%*
Precision	0.54
Recall	0.52
F1 - Score	**0.53**

Weighted F1-Score: 0.4705

Classification Report:

	precision	recall	f1-score	support
glioma	0.56	0.15	0.24	300
meningioma	0.49	0.31	0.38	306
notumor	0.63	0.82	0.71	405
pituitary	0.38	0.63	0.47	300
accuracy			0.51	1311
macro avg	0.51	0.48	0.45	1311
weighted avg	0.52	0.51	0.47	1311

ResNet50 F1 Score Table



ResNet50 Confusion Matrix

Statistical Evaluation Metrics:

To assess model performance, we used several key statistical metrics:

Accuracy: Measures the proportion of correctly classified instances among all cases.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision: Indicates how many of the positively predicted cases were correct.

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall (Sensitivity): Measures the ability of the model to detect true positive cases.

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1-score: A harmonic means of precision and recall, balancing false positives and false negatives.

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Loss Function: Measures the error during training, calculated using categorical cross-entropy.

$$\text{Loss} = -\sum(y \log(\hat{y}))$$

4.2 Confusion Matrix and Error Analysis

To further analyze performance, we used a **confusion matrix**, which includes:

- **True Positives (TP)**: Correctly identified tumor cases.
- **False Positives (FP)**: Non-tumor cases incorrectly classified as tumors.
- **True Negatives (TN)**: Correctly identified non-tumor cases.
- **False Negatives (FN)**: Tumor cases misclassified as non-tumors.

A high false positive rate can lead to unnecessary medical procedures, while a high false negative rate can result in missed diagnoses. By optimizing our models using Grad-CAM visualizations and hyperparameter tuning, we aimed to reduce these errors and improve classification performance.

InceptionV3 demonstrated superior accuracy (81.5%) and robustness.

AlexNet performed well but struggled with specific tumor types.

ResNet50 exhibited overfitting, leading to lower validation accuracy.

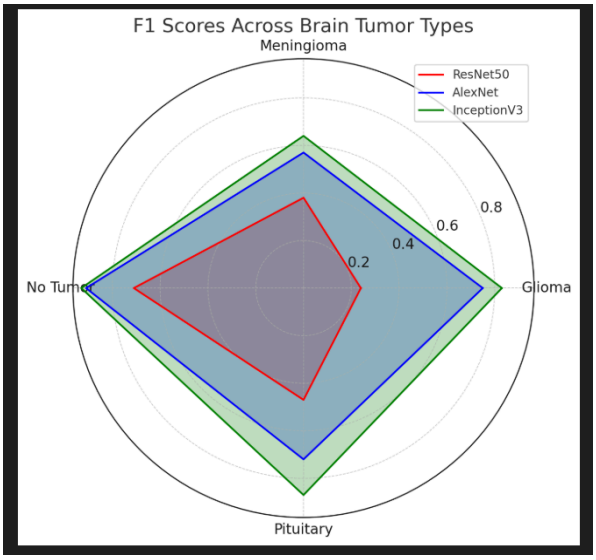
Evaluation metrics: Accuracy, F1-score, validation loss curves, and confusion matrices were analyzed.

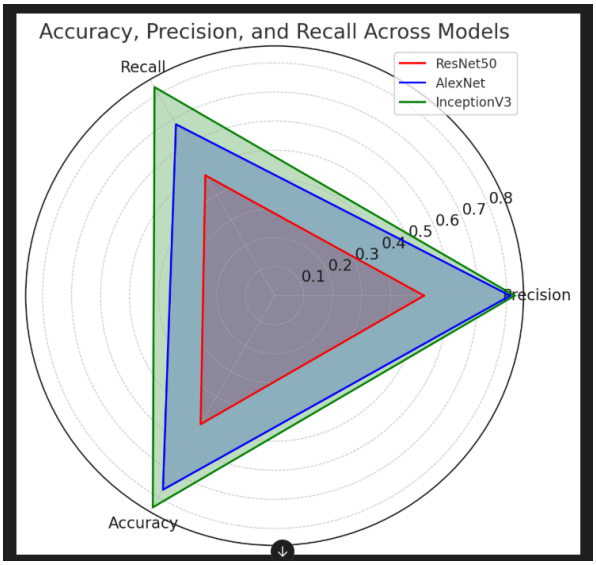
	A	B	C	D	E	F	G	H	I	J	K	L	M
1		**ResNet50**				**AlexNet**				**InceptionV3**			
2		***Precision***	***Recall***	***F1-Score***	***Support***	***Precision***	***Recall***	***F1-Score***	***Support***	***Precision***	***Recall***	***F1-Score***	***Support***
3	*Gliomla*	0.56	0.15	0.24	300	0.90	0.64	0.75	300	0.83	0.84	0.83	300
4	*Meningioma*	0.49	0.31	0.38	306	0.58	0.55	0.57	306	0.77	0.56	0.64	306
5	*No Tumor*	0.63	0.82	0.71	405	0.81	0.98	0.89	405	0.92	0.95	0.94	405
6	*Pituitary*	0.38	0.63	0.47	300	0.82	0.86	0.84	300	0.79	0.96	0.87	300
7	*Accuracy*			**0.51**	**1311**			**0.77**	**1311**			**0.84**	**1311**
8	*Macro Average*	0.51	0.48	0.45	1311	0.78	0.76	0.76	1311	0.83	0.83	0.82	1311
9	*Weighted Average*	0.52	0.51	0.47	1311	0.78	0.77	0.77	1311	0.83	0.84	0.83	1311

Discussion

Our experiments reveal that InceptionV3 outperforms AlexNet and ResNet50, achieving the highest accuracy of 81.5%. However, some key challenges remain:

- **Overfitting in ResNet50**: The model showed high variance between training and validation accuracy, suggesting that additional regularization techniques, such as dropout adjustments or L2 weight decay, could be beneficial.
- **Dataset Imbalance**: Certain tumor classes had fewer training samples, leading to misclassifications. Implementing synthetic data augmentation could mitigate this issue.
- **High False Positive Rate**: Some misclassifications occurred due to the model's tendency to over-predict certain tumor types. Adjusting class weights and fine-tuning decision thresholds may improve performance.





Future Work

To improve our model and extend its real-world applicability, we propose:

- **Expanding the dataset** by incorporating additional MRI scans from clinical sources.
- **Exploring ensemble learning** to combine the strengths of multiple models for improved classification accuracy.
- **Optimizing inference speed** to enable real-time classification in clinical settings.
- **Enhancing model explainability** through advanced interpretability techniques like SHAP and LIME.
- **Validating the model on external datasets** to assess its robustness and generalizability.

Conclusion

Deep learning provides a reliable approach for classifying brain tumors, with InceptionV3 demonstrating the highest accuracy and proving to be the most effective model. AlexNet achieved moderate results, making it suitable for identifying specific tumor types. ResNet50, despite its lower performance, can serve as a foundational model for further improvement by incorporating additional libraries and fine-tuning. Future enhancements, such as expanding the dataset and implementing ensemble learning, are recommended to optimize clinical applications.

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12. Presentation :קישור לגוגל דרייב