Brain Tumor Classification

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Date: Dec 6th, 2023

Abstract:

This project focuses on advancing brain tumor diagnosis through machine learning, employing TensorFlow to classify tumors based on imaging data. Motivated by the urgency of early detection in mitigating life-threatening issues, our dataset is made up of 3064 slices. The images are categorized as three different kinds of tumors: meningioma, glioma, and pituitary. We underwent data handling by including data augmentation and splitting for training, validation, and testing. Using a Convolution Neural Network (CNN) architecture and pre-trained models like Xception and ResNet50, the project demonstrates the potential to change the healthcare industry by using artificial intelligence. While it can still be improved, the superior performance of the Xception model, with its depth-wise separable convolutions and hierarchical feature learning, underscores its efficacy in discriminating between tumor and non-tumor cases, offering a reliable and efficient tool for healthcare practitioners. Once these models are fully finished, this will reduce diagnosis time and open avenues for prompt intervention and treatment planning.

Introduction:

Brain tumor diagnosis and classification have undergone a transformative shift with the advent of deep learning and artificial intelligence (AI) technologies. In recent years, the exponential growth in medical imaging datasets and the computational prowess of deep neural networks have paved the way for more accurate and efficient identification of brain tumors. This report delves into the development and application of advanced AI models designed for the classification of brain tumors, specifically focusing on meningioma, glioma, and pituitary tumors. Leveraging a rich dataset comprising 3064 T1-weighted contrast-enhanced images from 233 patients, this research aims to contribute to the grow rapidly in this field of medical image analysis, to provide a nuanced understanding of how deep learning methodologies enhance the diagnostic capabilities in the realm of neuroimaging.

Machine learning and medicine has spurred significant advancements in automating intricate medical tasks, like in the realm of brain tumor classification. By harnessing the power of deep neural networks, this study explores the nuances of tumor recognition and differentiation. The introduction of convolutional neural networks (CNNs) and other sophisticated deep learning architectures has not only expedited the diagnostic process but has also exhibited the potential to surpass human-level performance in certain scenarios. As we navigate through the intricacies of the developed AI models, we will unravel the underlying principles, methodologies, and key findings that contribute to the efficacy of these models in distinguishing between distinct brain tumor types.

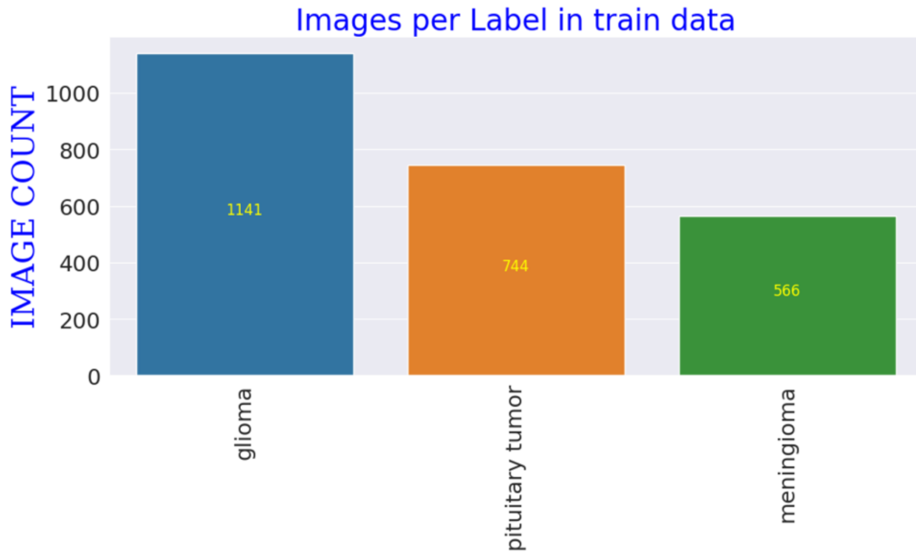
Motivation:

The motivation behind embarking on this endeavor lies in the critical need for more advanced and efficient tools in the domain of neuroimaging for brain tumor classification. Traditional diagnostic methods, while valuable, often rely heavily on manual interpretation and are subject to inter-observer variability. The integration of deep learning models offers a solution to these challenges by automating the process, enabling rapid and consistent tumor classification. The urgency of accurate and timely diagnoses in the realm of brain tumors underscores the significance of this research, as misclassifications or delays in identification can significantly impact patient outcomes. By harnessing the power of artificial intelligence, we aim to contribute to the ongoing efforts in advancing medical imaging technologies, improving the speed, accuracy, and reliability of brain tumor classification.

Objective:

The objective is to accurately classify MRI brain scans into one of three categories based on the presence and type of brain tumor: meningioma, glioma, or pituitary tumor. The dataset for this task includes 3064 MRI slices, distributed as 708 slices for meningioma, 1426 slices for glioma, and 930 slices for pituitary tumor. To achieve this, three distinct machine learning algorithms are utilized: a traditional Convolutional Neural Network (CNN), ResNet50, and Xception. Each of these models has been chosen for their proven effectiveness in image recognition tasks.

Data Preprocessing: Before training, the MRI slices would be preprocessed to normalize the pixel values, resize the images to fit the input size of the models, and augment the data to create a more robust dataset.



Training: Each model is trained on the dataset, using ReLU activations for hidden layers, SoftMax for the output layer, and incorporating dropout in the dense layers to combat overfitting.

Evaluation: The models are evaluated based on their ability to classify the MRI slices correctly. Performance metrics such as accuracy, precision, recall, and F1 score would be used to compare the effectiveness of each algorithm.

CNN provides a baseline model tailored specifically for this dataset, while ResNet50 and Xception offer advanced architectures with proven success in image classification tasks. The use of ReLU and SoftMax activations is standard practice, and the inclusion of dropout helps to ensure that the models generalize well to new, unseen data. The goal is to leverage the strengths of each model to achieve the highest possible accuracy in classifying the brain tumors.

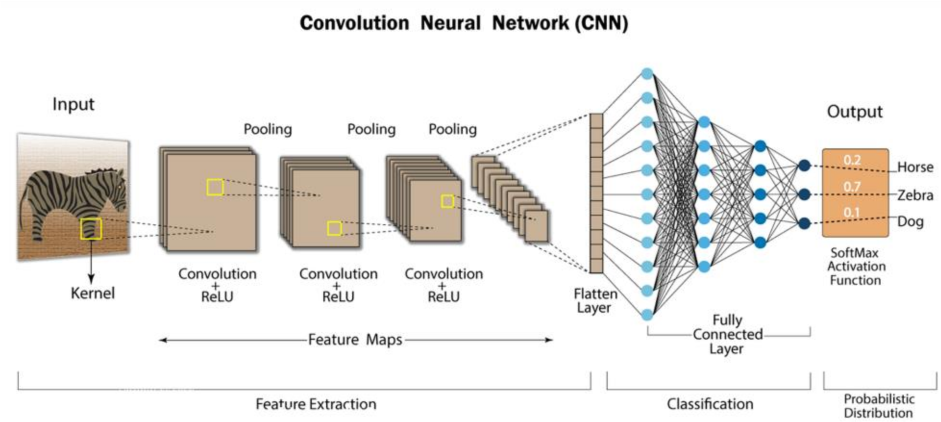
Related Works:

Many studies about brain tumor classification have made strides through research and one we want to focus on is Cheng's study, titled "Enhanced Performance of Brian Tumor Classification via Tumor Region Augmentation and Partition." They present an interesting approach to augmenting the tumor region within the brain images. This allows the images to be more visible and distinctive for improved accuracy in medical image analysis. This also allows a more detailed analysis of the tumor's internal structure, heterogeneity, and spatial distribution. For improved outcomes, shape, texture, and intensity variation contribute to enhanced brain tumor detection.

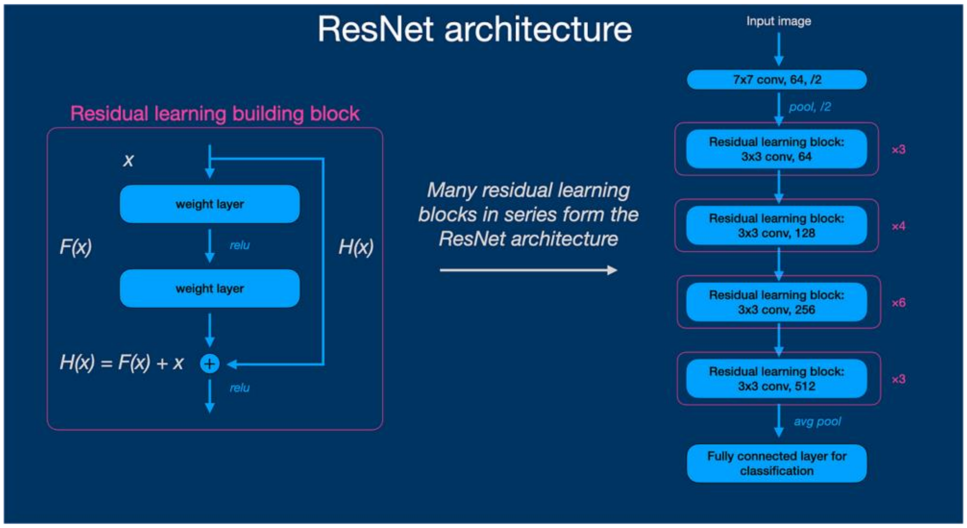
This study emphasizes exploring advanced techniques in image augmentation and segmentation. This aligns with our goals because both studies try to make their models more precise and efficient for brain tumor classification. By building upon these works, our project aims to further validate and extend the efficacy of such methodologies. By going deeper into their work, we seek to validate their effectiveness and the boundaries of innovation.

Architecture:

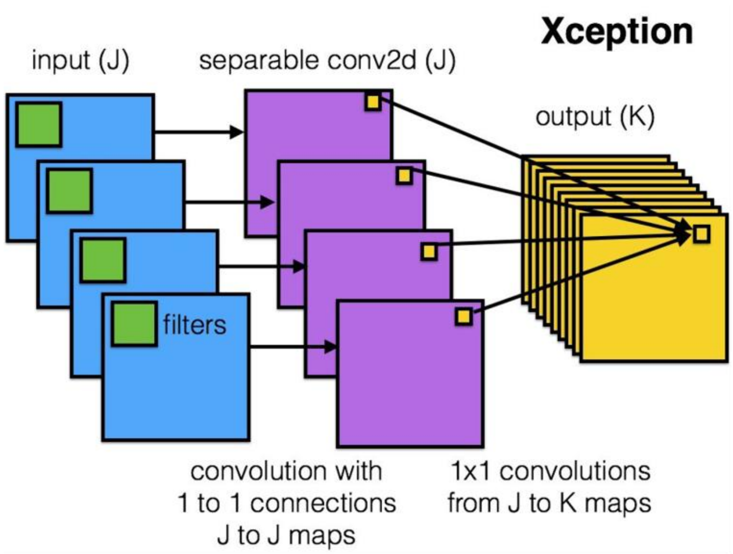
In neural network architectures, the Convolutional Neural Network (CNN) serves as a foundational framework for various computer vision tasks. The general CNN architecture encompasses an input layer for accepting data, particularly images in computer vision applications. Convolutional layers apply filters to detect features such as edges and textures while pooling layers down-sample spatial dimensions to reduce computation. Fully connected layers, typically found in the final layers, facilitate classification tasks by connecting neurons from the preceding layer. An activation function, often ReLU (Rectified Linear Unit), introduces non-linearity. CNNs find applications in tasks like image classification, object detection, and image segmentation, where labels are assigned to entire images or individual pixels.



ResNet50, a notable CNN variation, is based on a deep residual learning framework featuring residual blocks and shortcut connections. These connections skip one or more layers, addressing challenges in training very deep networks by facilitating gradient flow. With 50 layers in total, ResNet50 excels in tasks such as image classification, object detection, and feature extraction, particularly in transfer learning scenarios where pre-training on large datasets is advantageous.



Another prominent model, the Xception model, is derived from the Inception architecture. It employs depth wise separable convolutions, separating spatial and depth-wise convolution operations, and incorporates skip connections for improved information flow across layers. The key innovation lies in depth wise separable convolutions, reducing parameters and computation while capturing complex dependencies. Like ResNet50, Xception finds applications in image classification, object detection, and feature extraction.



Despite their differences, these models share commonalities as variations of CNNs tailored for specific purposes. Additionally, they often leverage pre-training on extensive datasets like ImageNet, utilizing transfer learning to fine-tune for specific tasks. This approach enhances their adaptability and efficiency in various computer vision applications.

Evaluation Results and Analysis:

CNN:

Confusion Matrix (Without Normalization)

```
[[143   0   0]
 [ 69   2   0]
 [ 84   2   7]]
```

- **Rows:** Actual classes.
- **Columns:** Predicted classes.
- Each cell value represents the count of instances.

Interpretation:

- **Glioma (Row 1):**
  - 143 instances were correctly predicted as glioma.
  - 0 instances of glioma were misclassified as meningioma or pituitary tumor.
- **Meningioma (Row 2):**
  - 69 instances of meningioma were misclassified as glioma.
  - 2 instances were correctly predicted as meningioma.
  - 0 instances of meningioma were misclassified as pituitary tumor.
- **Pituitary Tumor (Row 3):**
  - 84 instances of pituitary tumor were misclassified as glioma.
  - 2 instances were correctly predicted as pituitary tumor.
  - 7 instances of pituitary tumor were misclassified as meningioma.

Classification Report

- **Precision:** Proportion of correctly identified instances among the predicted instances.
- **Recall (Sensitivity):** Proportion of correctly identified instances among the actual instances.
- **F1-Score:** Harmonic meaning of precision and recall.
- **Support:** Number of actual occurrences of the class in the specified dataset.

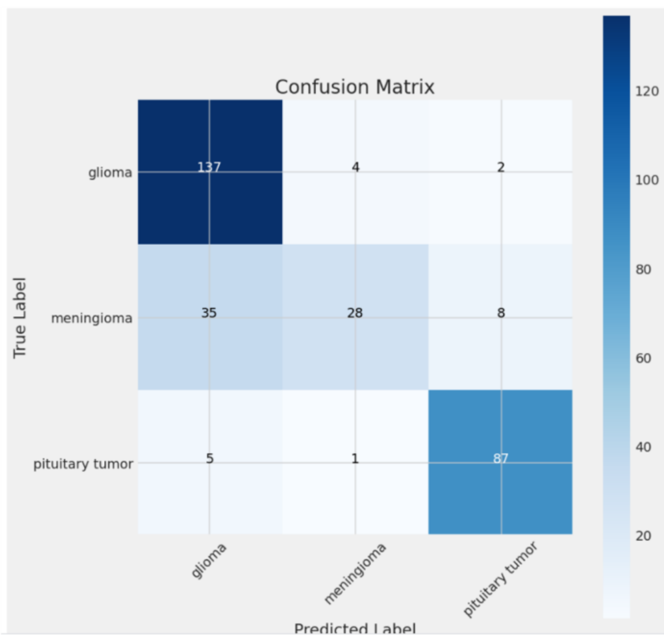
Overall Model Performance:

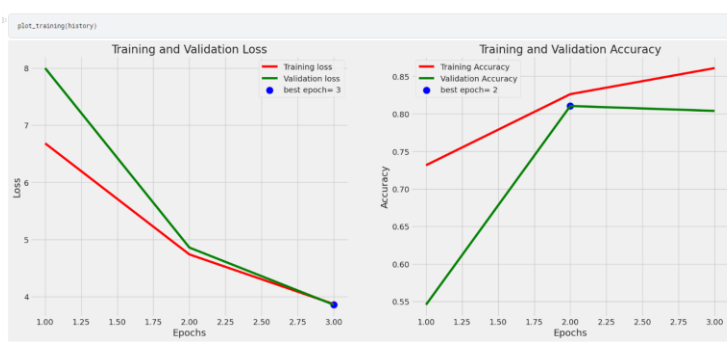
- **Accuracy:** 50% (overall correct predictions out of total predictions)
- **Precision:** Low across all classes, particularly for meningioma and pituitary tumor.
- **Recall:** Glioma has the highest recall, while meningioma and pituitary tumor have very low recall values.

- **F1-Score:** Generally low values, indicating a poor balance between precision and recall.

Summary:

The 2-layer CNN model's performance is quite inadequate compared to both Xception and ResNet50 models. It struggles significantly in correctly identifying instances across all classes, especially for meningioma and pituitary tumor classes, where it has notably low precision, recall, and F1-scores. The accuracy is also not satisfactory, suggesting the model needs substantial improvements, possibly through architecture modifications, increased layers, or data augmentation to improve its capability to generalize and identify these classes accurately.





ResNet50:

Confusion Matrix (Without Normalization)

```
[[96 47  0]
 [ 5 66  0]
 [38 55  0]]
```

- **Rows:** Actual classes.
- **Columns:** Predicted classes.
- Each cell value represents the count of instances.

Interpretation:

- **Glioma (Row 1):**
  - 96 instances were correctly predicted as glioma.
  - 47 instances of glioma were misclassified as meningioma.
  - 0 instances of glioma were predicted as pituitary tumor.
- **Meningioma (Row 2):**
  - 5 instances of meningioma were misclassified as glioma.
  - 66 instances were correctly predicted as meningioma.
  - 0 instances of meningioma were predicted as pituitary tumor.
- **Pituitary Tumor (Row 3):**
  - 38 instances of pituitary tumor were misclassified as glioma.
  - 55 instances of pituitary tumor were misclassified as meningioma.
  - 0 instances of pituitary tumor were predicted correctly.

Classification Report

- **Precision:** Proportion of correctly identified instances among the predicted instances.
- **Recall (Sensitivity):** Proportion of correctly identified instances among the actual instances.
- **F1-Score:** Harmonic mean of precision and recall.
- **Support:** Number of actual occurrences of the class in the specified dataset.

Overall Model Performance:

Accuracy: 53% (overall correct predictions out of total predictions)

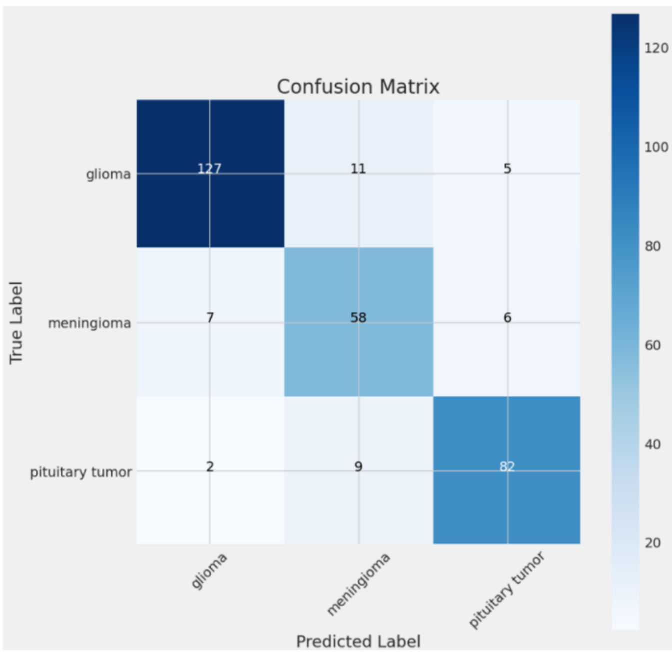
Precision: Relatively low across all classes.

Recall: Mixed; high for meningioma but very low for pituitary tumor.

F1-Score: Generally low values, indicating a poor balance between precision and recall.

Summary:

The ResNet50 model's performance is less satisfactory compared to the Xception model. It struggles notably in classifying pituitary tumors, where it fails to make any correct predictions. The overall accuracy is relatively low, and the model has significant challenges in correctly identifying instances across all classes, especially for the pituitary tumor class. This model might require further tuning, adjustments in class balancing, or potentially additional data to improve its performance on this specific classification task.



Xception Model:

Confusion Matrix (Without Normalization)

```
[[139   4   0]
 [  5  66   0]
 [  0   6  87]]
```

- **Rows** represent the true classes (actual labels).
- **Columns** represent the predicted classes by the model.
- Each cell in the matrix shows the count of instances.

Interpretation:

- **Glioma (Row 1):**
  - 139 instances were correctly predicted as glioma.
  - 4 instances of glioma were misclassified as meningioma.
  - 0 instances of glioma were misclassified as pituitary tumors.
- **Meningioma (Row 2):**
  - 5 instances of meningioma were misclassified as glioma.
  - 66 instances were correctly predicted as meningioma.
  - 0 instances of meningioma were misclassified as pituitary tumor.
- **Pituitary Tumor (Row 3):**
  - 0 instances of pituitary tumor were misclassified as glioma.
  - 6 instances of pituitary tumor were misclassified as meningioma.
  - 87 instances were correctly predicted as pituitary tumor.

Classification Report

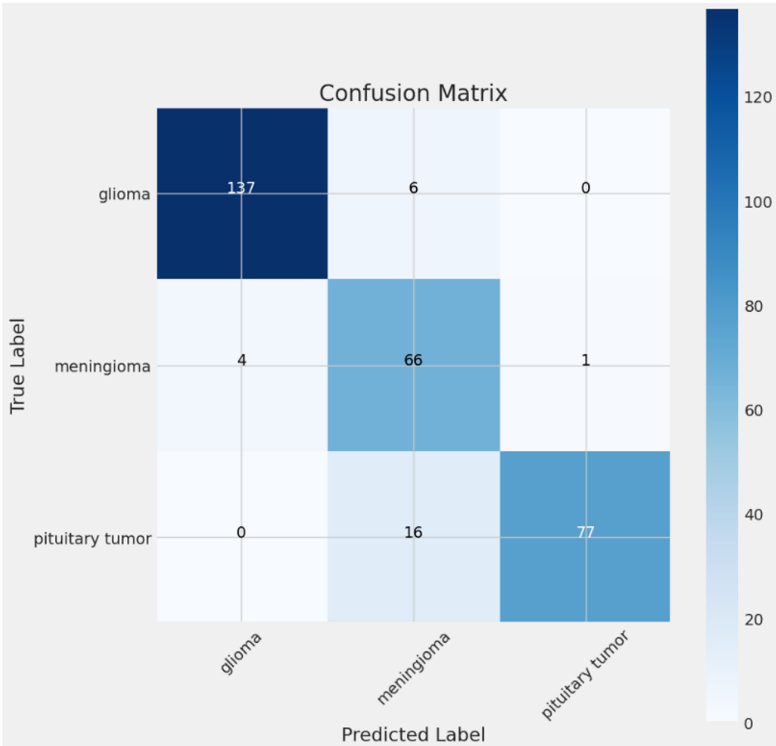
- **Precision:** Indicates the proportion of correctly identified instances among the predicted instances.
- **Recall (Sensitivity):** Indicates the proportion of correctly identified instances among the actual instances.
- **F1-Score:** The harmonic mean of precision and recall.
- **Support:** The number of actual occurrences of the class in the specified dataset.

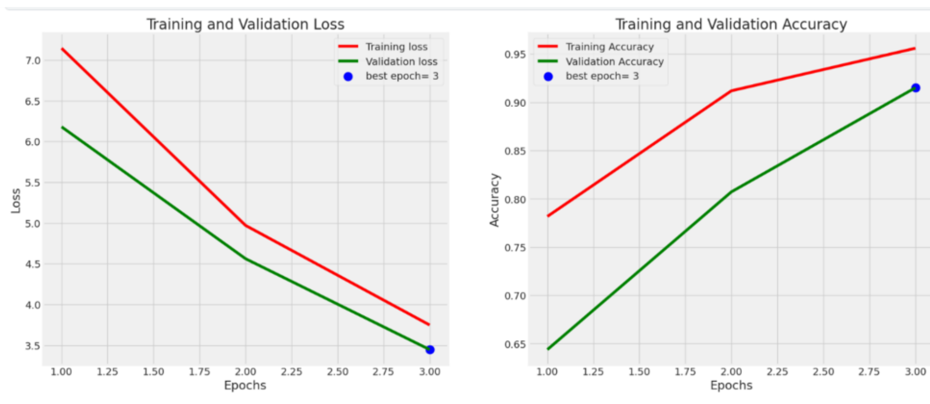
Overall Model Performance:

- **Accuracy:** 95% (overall correct predictions out of total predictions)
- **Precision:** High for all classes, indicating low false-positive rates.
- **Recall:** Generally high, indicating low false-negative rates.
- **F1-Score:** High values, suggesting good balance between precision and recall.

Summary:

The Xception model shows robust performance across all classes, with high accuracy and balanced precision and recall scores. It exhibits notable accuracy in classifying glioma and pituitary tumor classes, while slightly lower but still robust performance for meningioma classification. Overall, it is a well-performing model for this classification task.





Lessons Learned:

Model Selection Significance:

The Comparative analysis between Xception, ResNet50, and a generic Convolutional Neural Network (CNN) revealed that the choice of the underlying model architecture significantly impacts brain tumor classification performance.

Challenges Of Very Deep Networks:

ResNet50, while effective, faced challenges associated with vanishing gradients and optimization difficulties in very deep networks. This observation underscores the importance of considering network depth and gradient flow in model design.

Importance of Data Augmentation:

Augmenting the dataset through techniques like rotation, flipping, zooming, and rescaling proved crucial in enhancing the diversity of the training set, contributing to the model's ability to generalize unseen data.

Efficiency of Pre-Trained Models:

Leveraging pre-trained models like Xception and ResNet50 provided a solid foundation for our brain tumor classification task. These models, already trained on large datasets, accelerated the convergence of our model during training.

Contribution to healthcare:

The project reinforced the transformative potential of artificial intelligence in healthcare. Swift and accurate brain tumor detection not only improves patient outcomes but also underscores the crucial role of AI in advancing medical diagnostics.

Conclusion:

In summary, our project has delved into the intricacies of neural network architectures, with a primary focus on the Convolutional Neural Network (CNN), ResNet50, and the Xception model. Throughout this exploration, several key contributions have emerged, shaping the significance and impact of our endeavors. Firstly, our project underscores the foundational importance of CNNs in computer vision, serving as a versatile framework for tasks ranging from image classification to object detection and image segmentation. This foundational understanding establishes a solid basis for comprehending more advanced architectures.

Secondly, the integration of ResNet50 into our study has unveiled the power of deep residual learning. The introduction of shortcut connections and residual blocks addresses challenges associated with training extremely deep networks, paving the way for advancements in image classification, object detection, and feature extraction. The third and most intriguing contribution lies in the exploration of the Xception model. This innovative architecture, rooted in the Inception framework, introduces depth-wise separable convolutions, and skip connections. The utilization of depth-wise separable convolutions significantly reduces parameters and computation, showing an interesting approach to capturing complex dependencies in computer vision tasks.

Our project not only contributes to the understanding of these specific neural network architectures but also highlights their applications and innovations. The continual evolution of these models, coupled with the utilization of pre-training on extensive datasets, exemplifies the potential of transfer learning in enhancing adaptability and efficiency for specific computer vision applications. As we conclude, these contributions collectively affirm the dynamic nature of neural network architectures, driving advancements in artificial intelligence and computer vision.

Group Contributions:

Cristian Biondi - Research and Data:

Research Exploration:

- Explored foundational AI literature.
- Summarized key principles relevant to brain tumor classification.

Data Preparation:

- Led data preprocessing tasks.
- Ensured dataset cleanliness and augmentation for optimal model training.

Darwin Sadineni - Model Implementation and Analysis:

Model Development:

- Implemented machine learning models using TensorFlow.
- Coded the Convolutional Neural Network (CNN) architecture.
- Integrated pre-trained models (Xception, ResNet50).

Results Analysis:

- Led the analysis of model training and validation results.
- Interpreted metrics like accuracy, loss, and confusion matrices.

Anirudh Ravipudi - Data Processing and Presentation:

Data Augmentation:

- Specialized in data processing and augmentation.
- Ensured diversity and robustness in the training set.

Presentation:

- Led the creation of an engaging PowerPoint presentation.
- Translated technical details into accessible language with clear visuals.

Rahul Ravi - Research Collaborator and Model Implementation:

Research Collaboration:

- Collaborated with Cristian in exploring foundational AI concepts.

Model Implementation:

- Actively contributed to coding the CNN architecture.
- Fine-tuned parameters for optimal model performance.

Kashif Uddin - Results Analysis and Presentation:

Results Interpretation:

- Collaborated with all in analyzing model training and validation results.
- Provided valuable insights into model performance.

Presentation:

- Helped in creating a compelling PowerPoint presentation.
- Ensured clear communication of project objectives and outcomes.

Bibliography:

Cheng, J., Huang, W., Cao, S., Yang, R., Yang, W., Yun, Z., Wang, Z., & Feng, Q. (n.d.). Correction: Enhanced performance of brain tumor classification via tumor region augmentation and partition. PLOS ONE. https://journals.plos.org/plosone/article?id=10.1371%2Fjournal.pone.0144479

Shahriar, N. (2023, February 1). *What is Convolutional Neural Network-CNN (deep learning)*. Medium. https://nafizshahriar.medium.com/what-is-convolutional-neural-network-cnn-deep-learning-b3921bdd82d5

Xception architectural design. Xception Architectural Design - coding. (n.d.). https://stephan-osterburg.gitbook.io/coding/coding/ml-dl/tensorfow/ch3-xception/xception-architectural-design