Brain Tumor Classification from MRI Images Using a Custom CNN, XceptionNet, EfficientNet-B0, and Vision Transformer with Explainable AI Analysis

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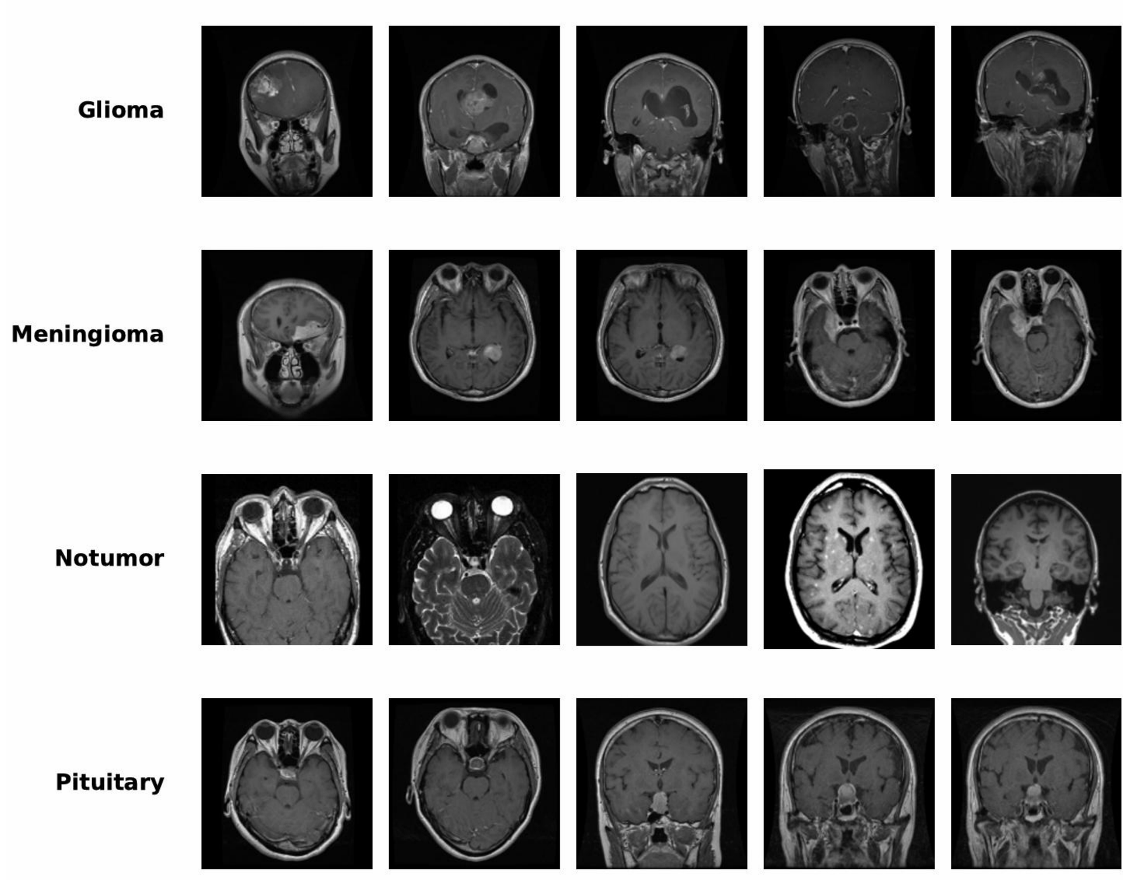
Introduction: Problem Statement

- Early detection saves lives.
- Manual MRI: slow & subjective.
- Deep learning: fast & accurate diagnosis.
- Challenge: Data & explainability lacking.
- This study compares CNN, XceptionNet, EfficientNet-B0, ViT, and applies XAI (Grad-CAM) for transparent diagnosis.

Introduction: Dataset



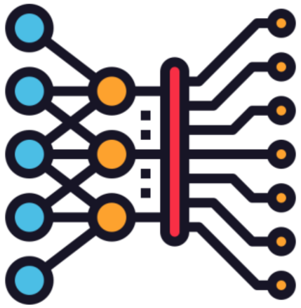
- Brain Tumor MRI Dataset released by kaggle
- Source: https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset/data
- 4 classes:
  - glioma
  - meningioma
  - no tumor
  - pituitary
- Size:
  - Testing Set : 1311
  - Training Set: 5712

Introduction: Research Questions

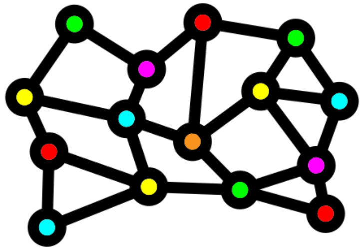
1. How do the ViT, XceptionNet, EfficientNet-B0, and a basic CNN differ in terms of accuracy, precision, recall, and other key performance metrics when detecting brain tumors from MRI images?
2. How does model complexity (such as number of parameters and computational cost) or architectural choice (CNN vs Transformer) influence the performance and efficiency of these models in brain tumor detection?
3. Which tumor types are most frequently misclassified by each model, and what patterns or trends can be observed from the confusion matrices and class-wise metrics?
4. How does the accuracy of the basic CNN model change as the number of training epochs increases (in steps of 10 up to 100), and what can we learn from this trend about the training needs of a simple CNN for brain tumor detection?
5. What insights can be gained from Grad-CAM visualizations about the decision-making process of each CNN-based model for brain tumor detection?

Introduction: Using Techniques

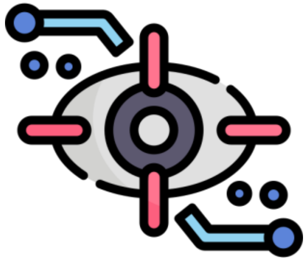
Convolutional Neural Networks



XceptionNet



EfficientNet-B0



Vision Transformer

eXplainable AI

Literature Review

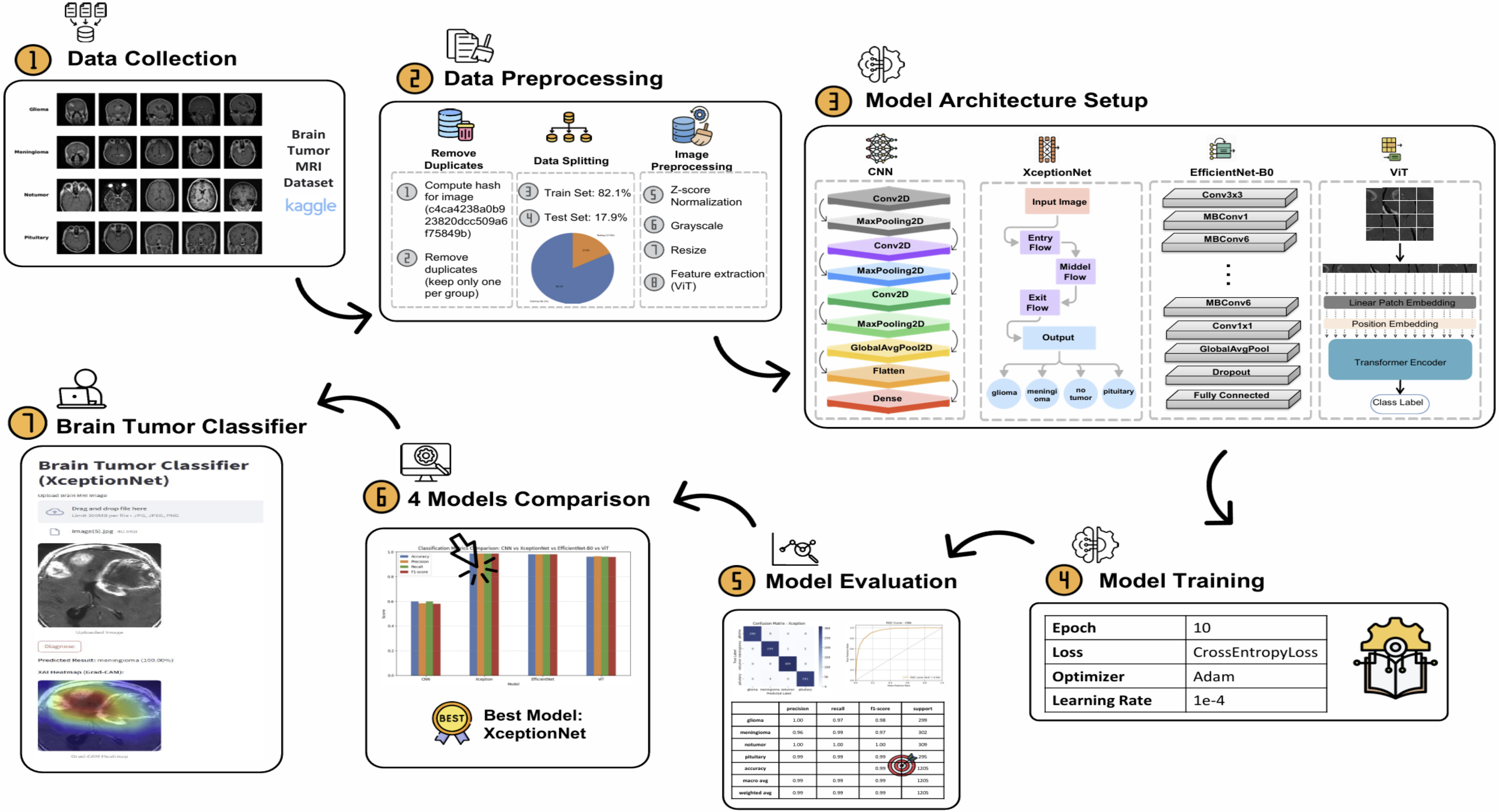
Literature Review

- *Yoon et al. (2025)* [1] demonstrated that a hybrid ensemble combining **Xception** and parallel deep **CNNs** achieved a 99.09% accuracy for four-class brain tumor classification, surpassing other state-of-the-art models such as VGG19 and ResNet152V2.
- *Verma et al. (2024)* [2] reported that a fine-tuned **Xception** model using the Kaggle dataset achieved approximately 98% training accuracy along with high precision, recall, and F1-score.
- *Shah et al. (2022)* [3] demonstrated that a fine-tuned **EfficientNet-B0** model, when combined with image enhancement and data augmentation, achieved an overall accuracy of 98.87%, outperforming VGG16, InceptionV3, **Xception**, ResNet50, and InceptionResNetV2.
- *Hossain et al. (2023)* [4] compared several transfer learning and deep learning models for brain tumor classification, including **ViT**, and found that the proposed IVX16 ensemble achieved the highest accuracy of 96.94% among all evaluated methods.

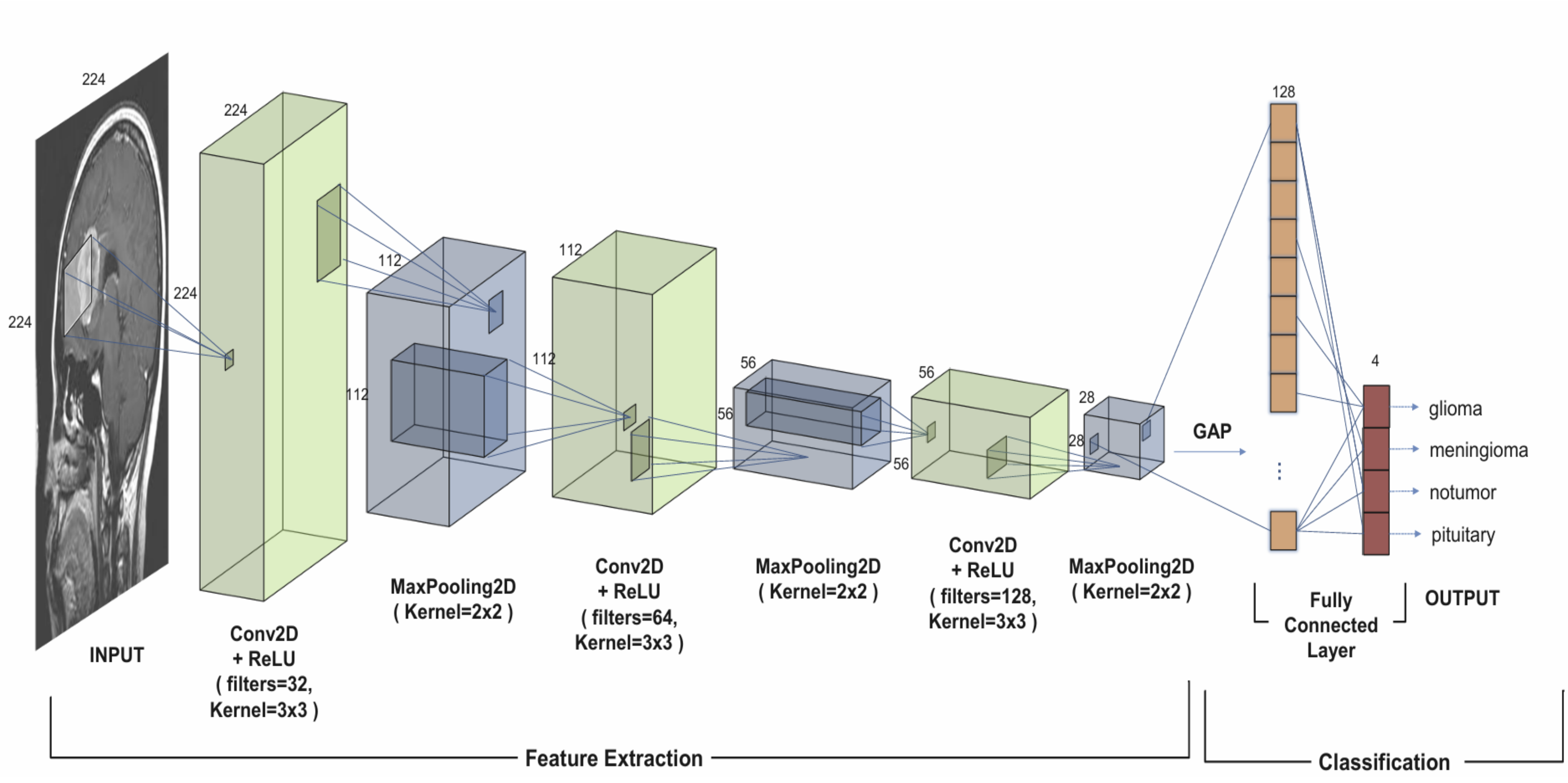
Methodology

- Workflow
- Network Architecture
- Network Configuration

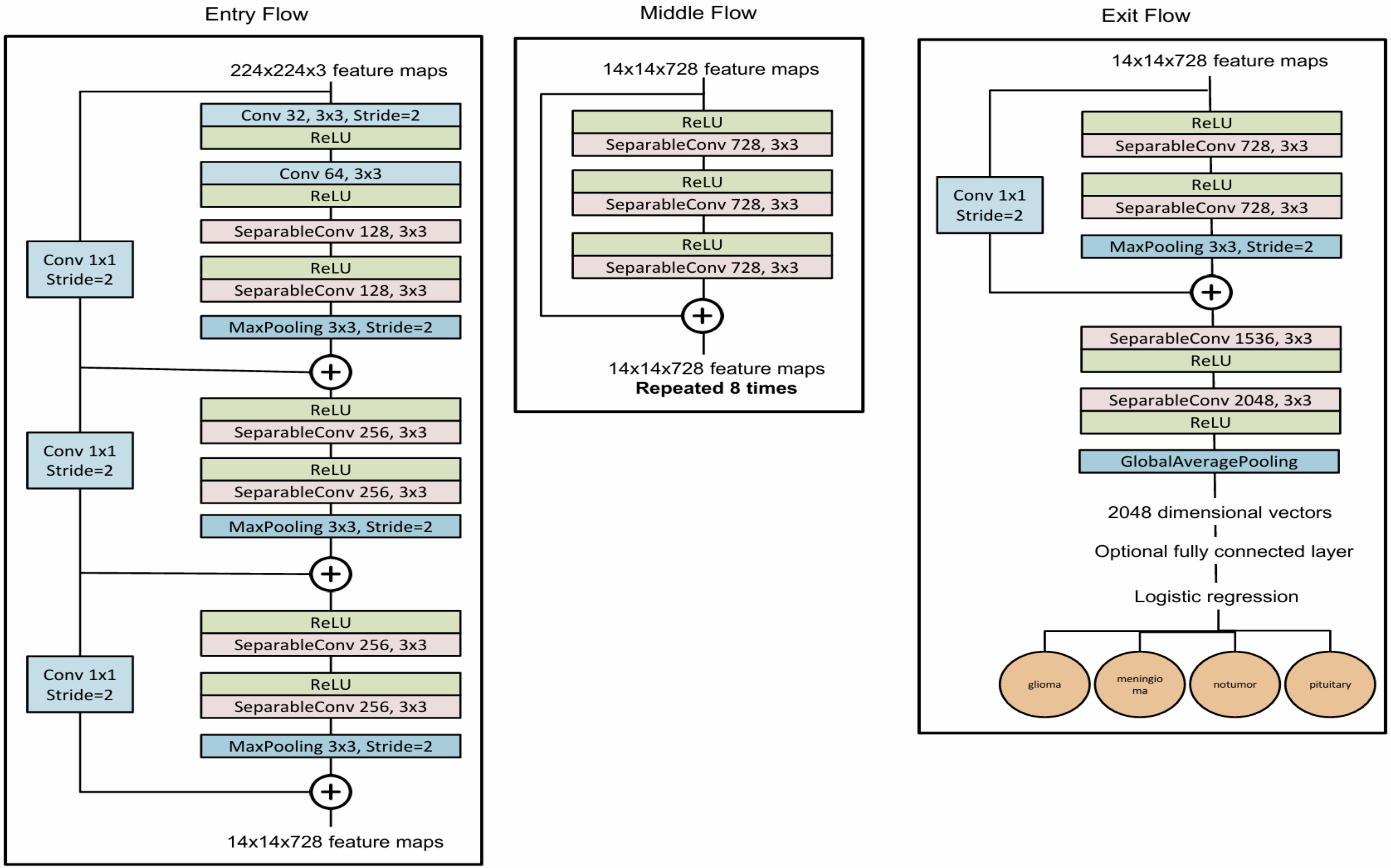
Methodology: Workflow



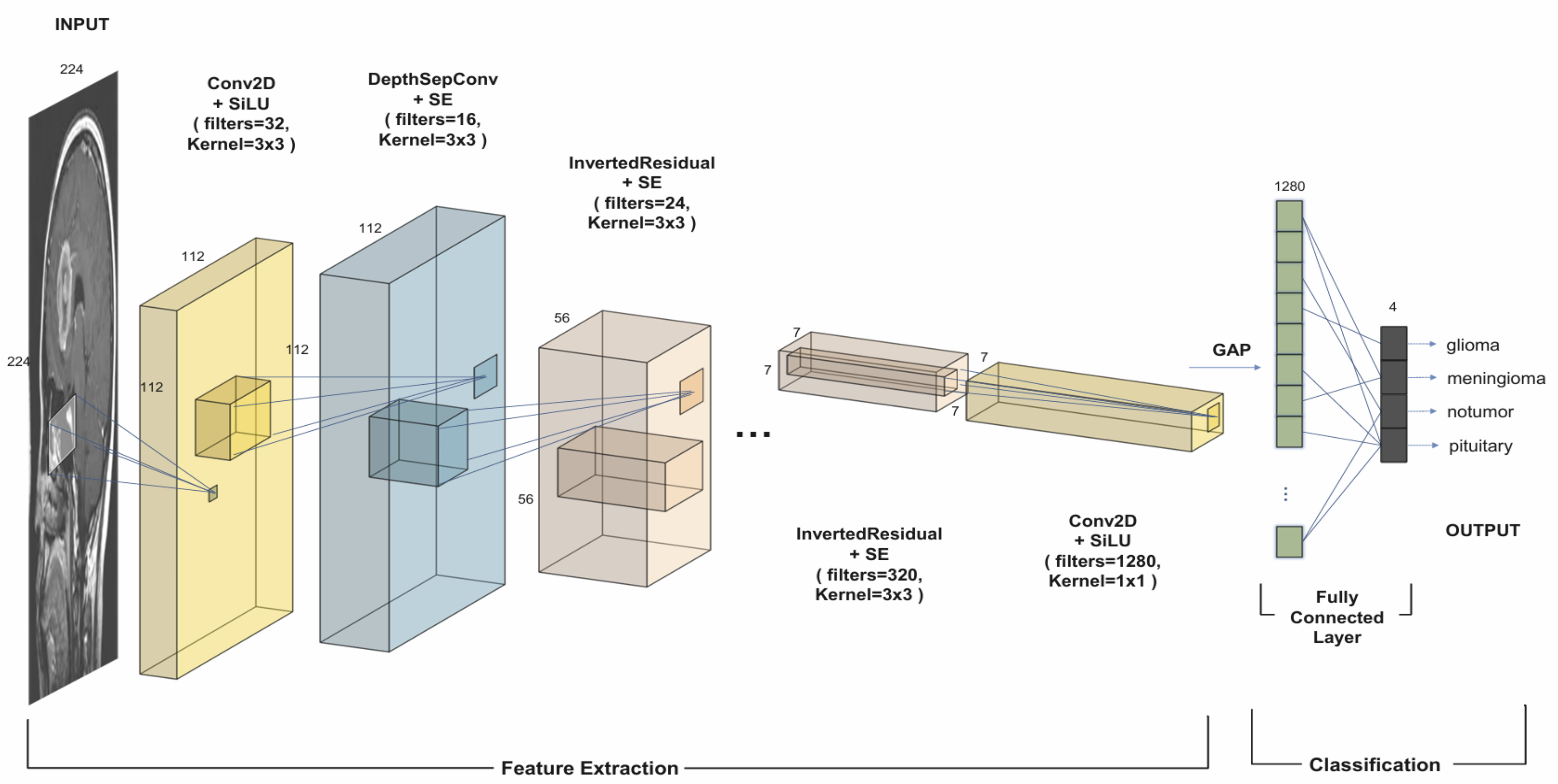
Methodology: Network Architecture (CNN)



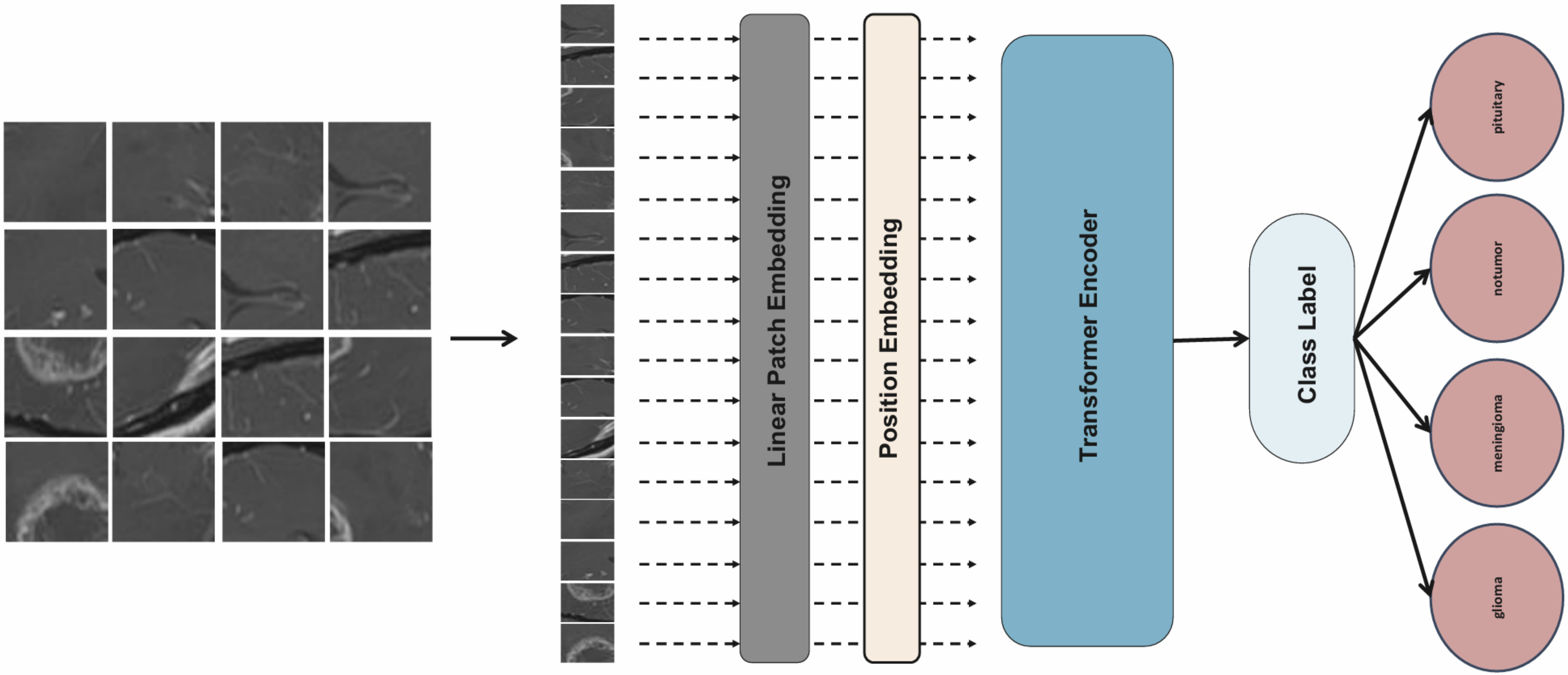
Methodology: Network Architecture (XceptionNet)



Methodology: Network Architecture (EfficientNet-B0)



Methodology: Network Architecture (Vision Transformer)



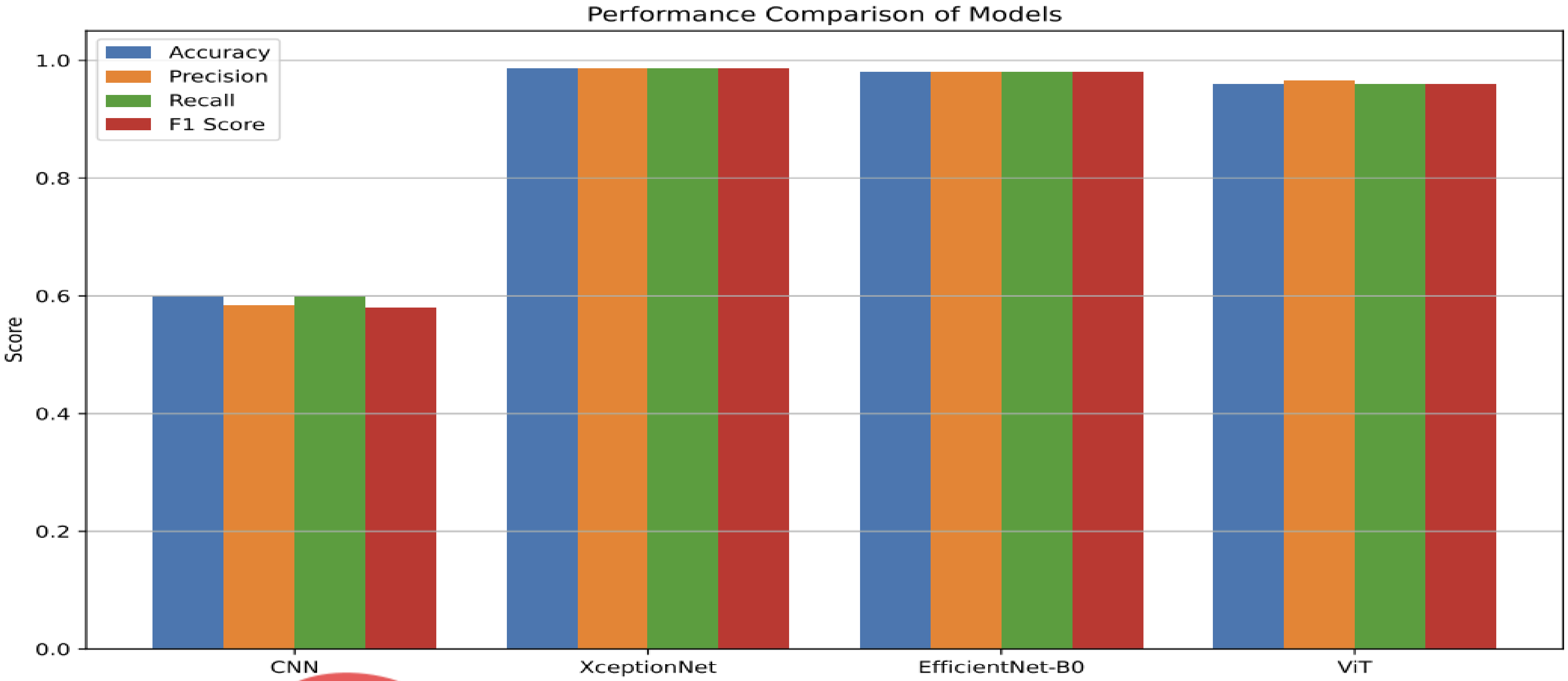
Methodology: Network Configuration

Network Configuration	
Epochs	10
Learning rate	0.0001
batch size(train/val/test)	32/64/64
Optimizer	Adam
Loss	CrossEntropyLoss
num_classes	4

Results and Discussion

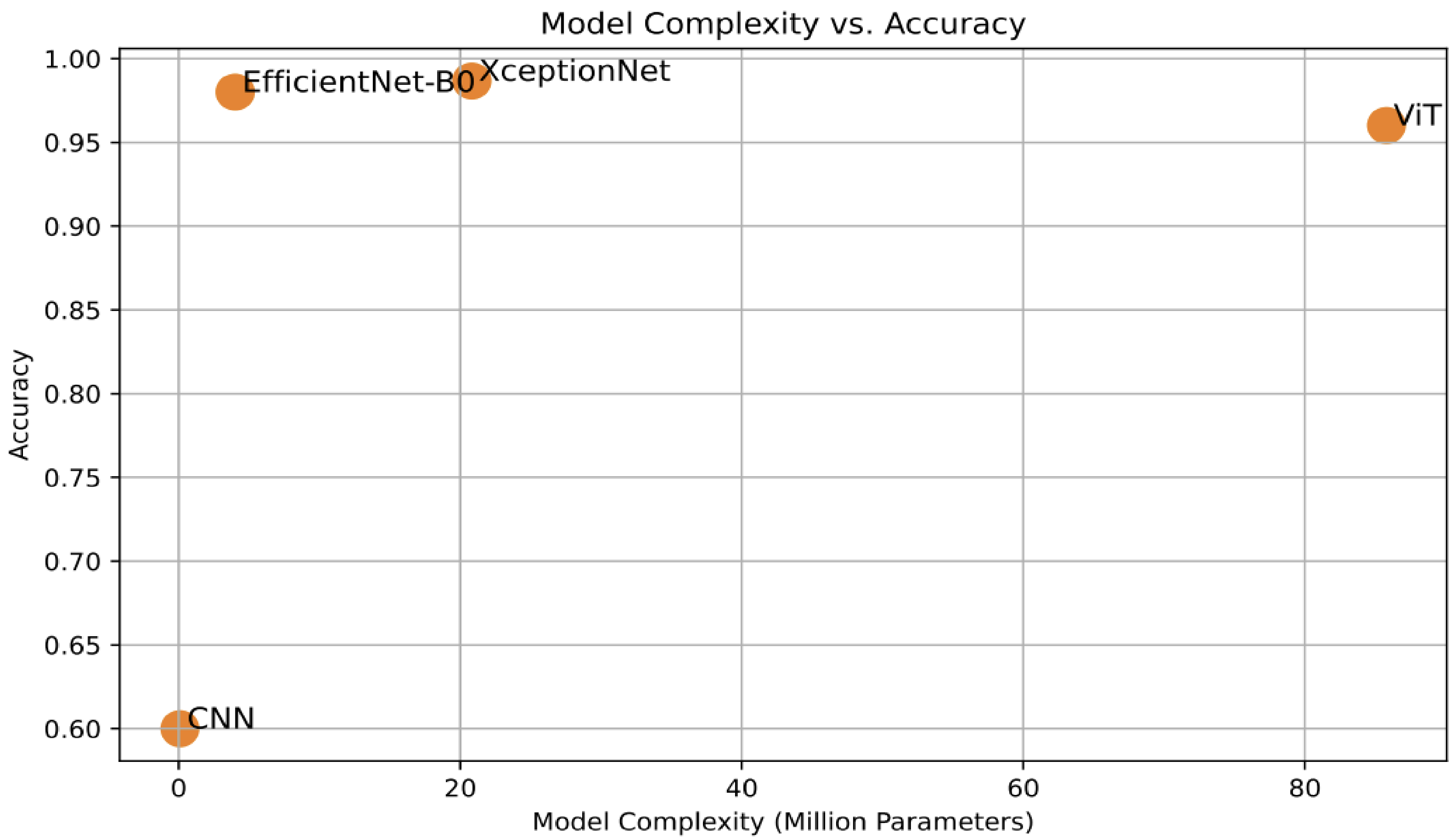
- Model Performance Comparison
- Complexity vs. Efficiency
- Misclassification Patterns
- CNN Training Epoch Analysis
- Grad-CAM Visualization Insights

Results and Discussion: Model Performance Comparison



Model	Accuracy	Precision (Weighted)	Recall (Weighted)	F1-score (Weighted)	Precision (Macro)	Recall (Macro)	F1-score (Macro)
CNN	0.6	0.5835	0.6	0.5808	0.5838	0.6004	0.5812
XceptionNet	0.9867	0.9871	0.9867	0.9868	0.9871	0.9866	0.9867
EfficientNet-B0	0.9801	0.9802	0.9801	0.98	0.9802	0.98	0.98
ViT	0.9602	0.9653	0.9602	0.96	0.9653	0.9598	0.9599

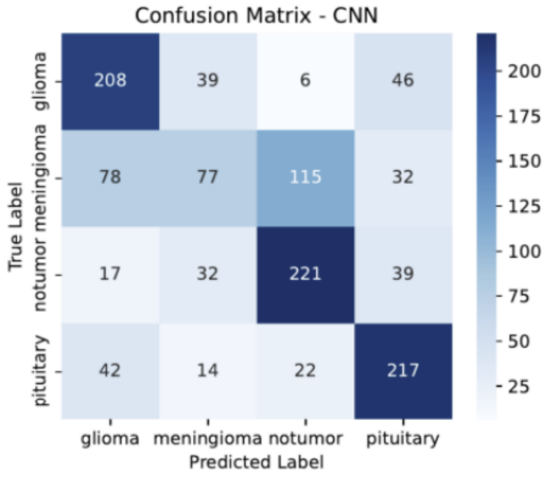
Results and Discussion: Complexity vs. Efficiency



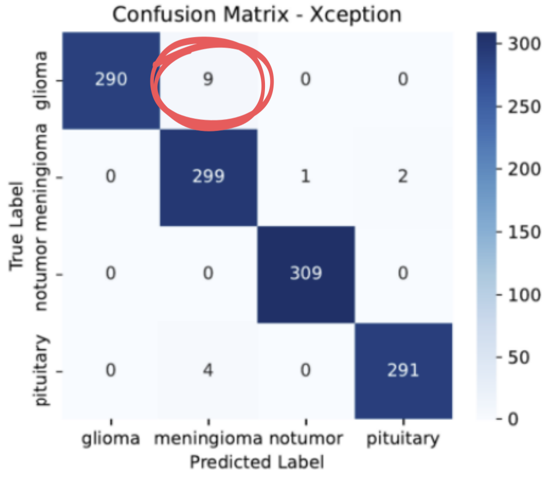
Model	Params (M)	FLOPs (G)	Training Time (min)
CNN	0.09	0.52	6.01
XceptionNet	20.82	4.6	16
EfficientNet-B0	4.01	0.39	6.62
ViT	85.8	16.87	33.51

Results and Discussion: Misclassification Patterns

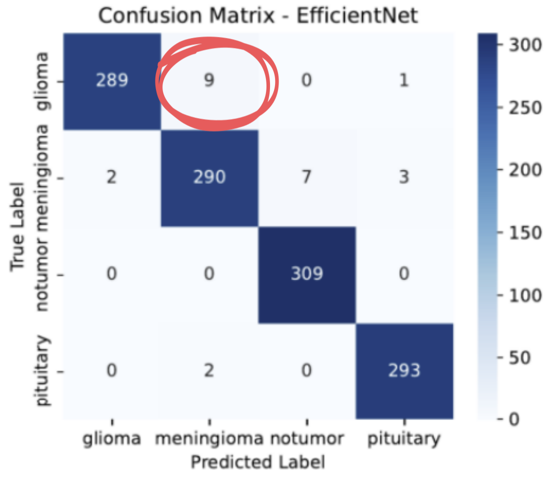
CNN



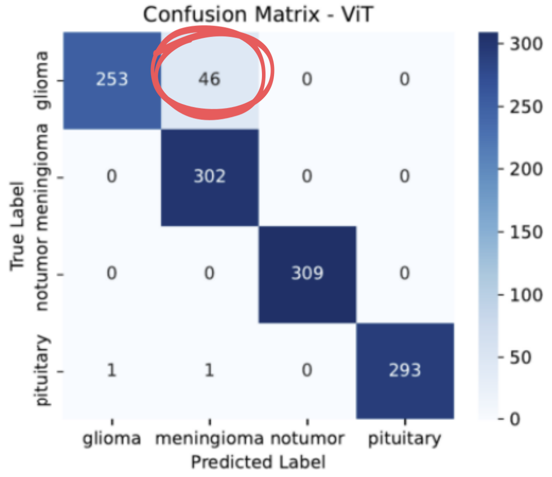
XceptionNet



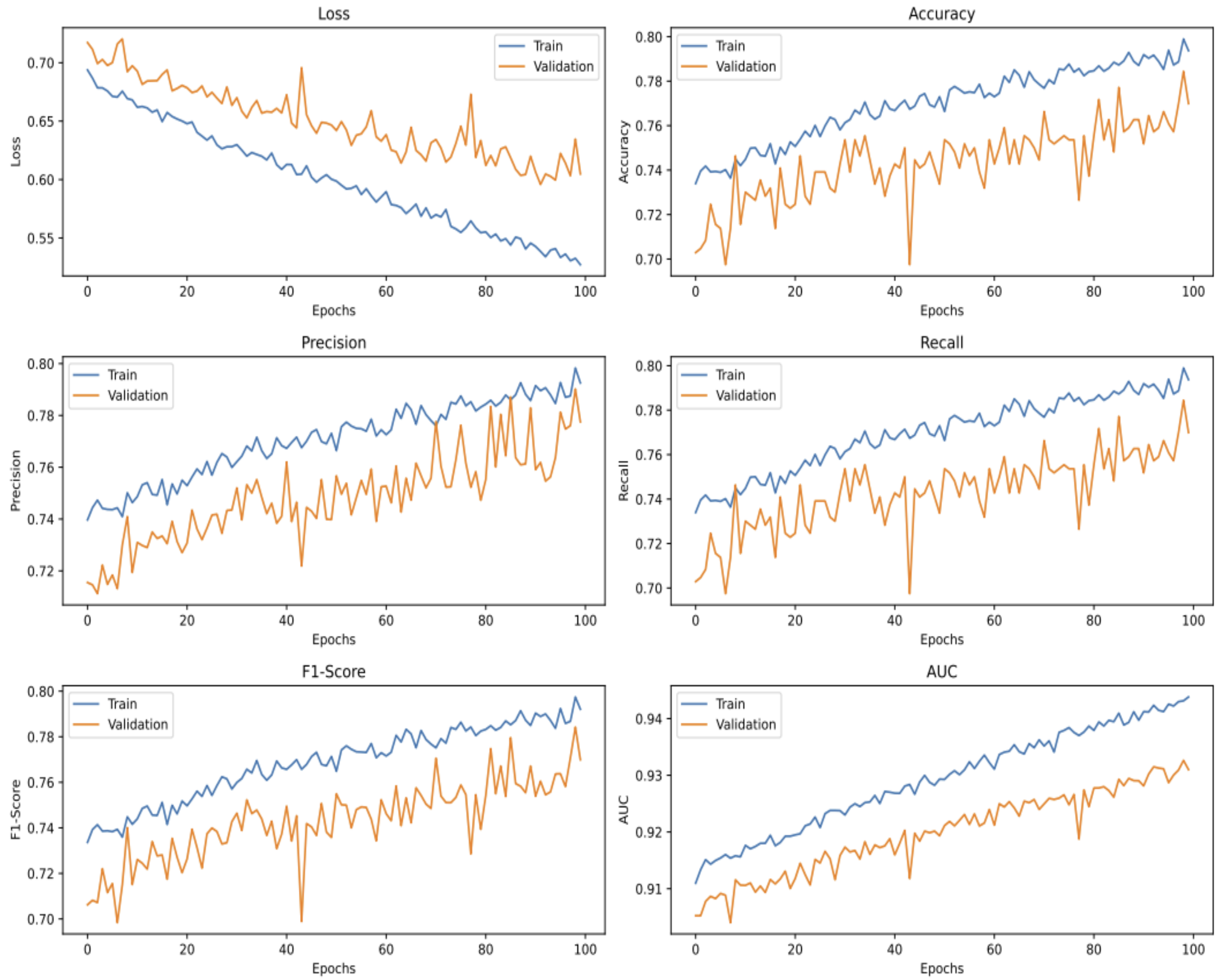
EfficientNet-B0



Vision Transformer



Results and Discussion: CNN Training Epoch Analysis



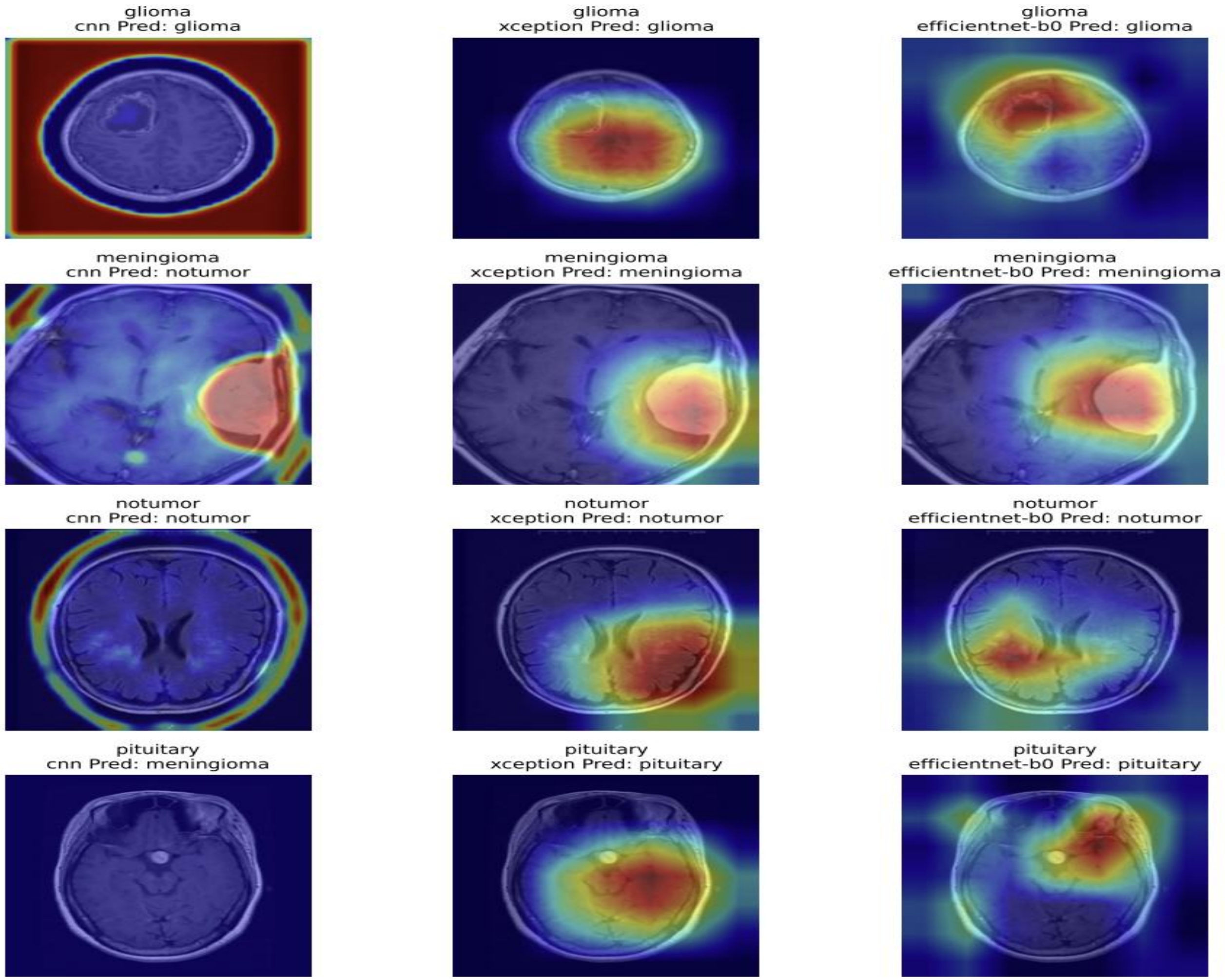

```
[Epoch 1] Train Acc: 0.7340, Val Acc: 0.7029
[Epoch 2] Train Acc: 0.7396, Val Acc: 0.7047
[Epoch 3] Train Acc: 0.7418, Val Acc: 0.7083
[Epoch 4] Train Acc: 0.7392, Val Acc: 0.7246
[Epoch 5] Train Acc: 0.7394, Val Acc: 0.7156
[Epoch 6] Train Acc: 0.7390, Val Acc: 0.7138
[Epoch 7] Train Acc: 0.7402, Val Acc: 0.6975
[Epoch 8] Train Acc: 0.7364, Val Acc: 0.7138
[Epoch 9] Train Acc: 0.7450, Val Acc: 0.7464
[Epoch 10] Train Acc: 0.7420, Val Acc: 0.7156
```

⋮

```
[Epoch 91] Train Acc: 0.7919, Val Acc: 0.7518
[Epoch 92] Train Acc: 0.7903, Val Acc: 0.7645
[Epoch 93] Train Acc: 0.7917, Val Acc: 0.7572
[Epoch 94] Train Acc: 0.7889, Val Acc: 0.7591
[Epoch 95] Train Acc: 0.7853, Val Acc: 0.7663
[Epoch 96] Train Acc: 0.7939, Val Acc: 0.7609
[Epoch 97] Train Acc: 0.7873, Val Acc: 0.7572
[Epoch 98] Train Acc: 0.7887, Val Acc: 0.7699
[Epoch 99] Train Acc: 0.7990, Val Acc: 0.7844
[Epoch 100] Train Acc: 0.7937, Val Acc: 0.7699
```

Results and Discussion: Grad-CAM Visualization Insights

CNN | **XceptionNet** | **EfficientNet-B0**



- **CNN** Grad-CAM analysis shows a tendency to highlight not only the tumor area but also surrounding brain tissue and background regions.

- **XceptionNet** and **EfficientNet-B0** accurately focus on the tumor region without highlighting irrelevant surrounding areas, showing precise and reliable localization.

Limitations

- Limited tumor classes & dataset generalizability
- Fixed hyperparameters
- Qualitative XAI only (Grad-CAM)
- Clinical noise & variability not considered
- Limited Transformer tuning (resource limits)
- Possible subjective interpretation

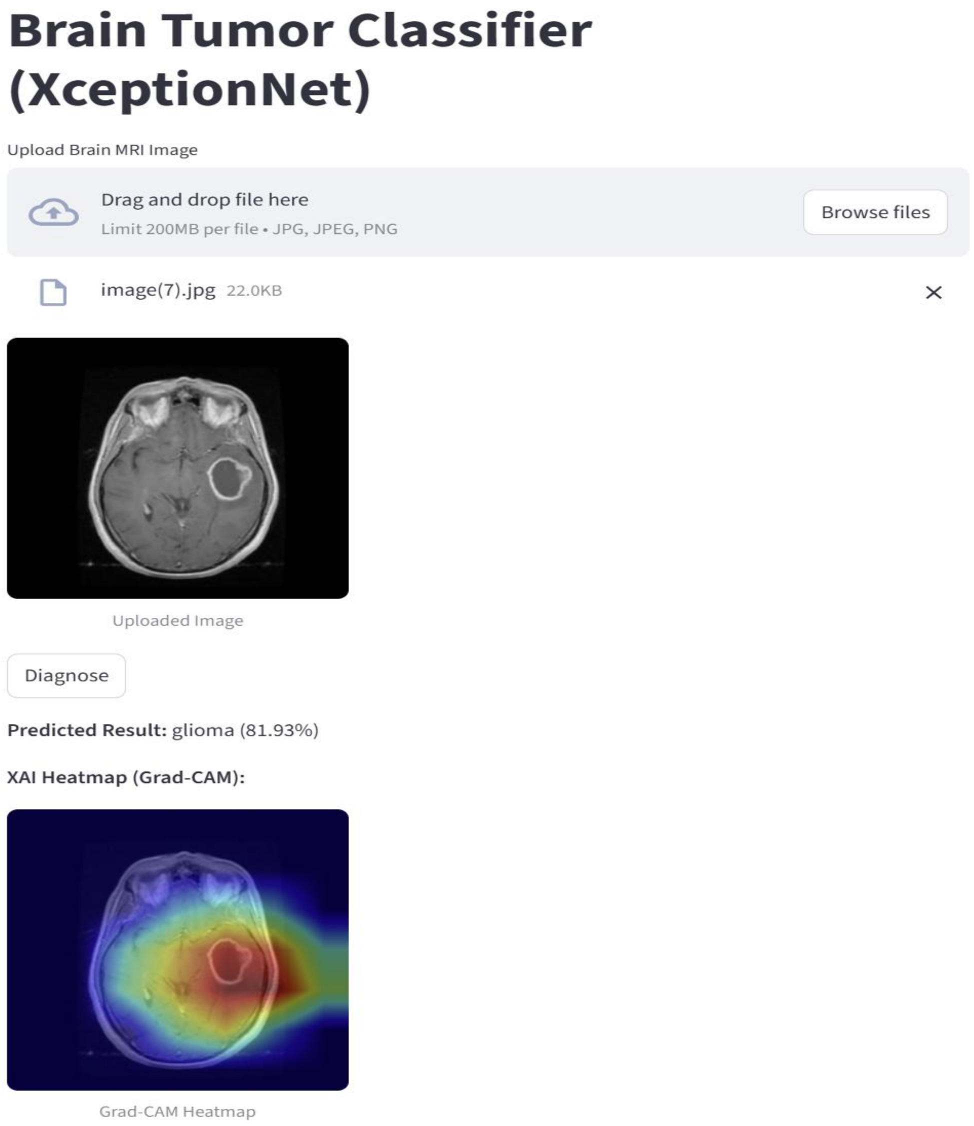
Future Directions

- Use multi-institutional MRI data
- Hyperparameter tuning
- Combine XAI with quantitative analysis
- Explore new hybrid and ensemble models
- Develop clinical workflow integration & user feedback systems
- Build personalized AI diagnostics using patient data

Demonstration

Demonstration

- Demo URL: https://braintumorclassification-ofjem34wtqqbrwbrxsgggj.streamlit.app/
- Frontend: Streamlit
- Using Model: XceptionNet



References

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[1] S. Yoon, “Brain tumor classification using a hybrid ensemble of xception and parallel deep cnn models,” Informatics in Medicine Unlocked, vol. 54, p. 101629, 2025.

[2] G. Verma, “Xception-based deep learning model for precise brain tumour classification,” in 2024 8th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC). IEEE, 2024, pp. 1481–1485.

[3] H. A. Shah, F. Saeed, S. Yun, J.-H. Park, A. Paul, and J.-M. Kang, “A robust approach for brain tumor detection in magnetic resonance images using finetuned efficientnet,” Ieee Access, vol. 10, pp. 65 426–65 438, 2022.

[4] S. Hossain, A. Chakrabarty, T. R. Gadekallu, M. Alazab, and M. J. Piran, “Vision transformers, ensemble model, and transfer learning leveraging explainable ai for brain tumor detection and classification,” IEEE Journal of Biomedical and Health Informatics, vol. 28, no. 3, pp. 1261–1272, 2023.

Thank you