DEEP LEARNING BASED BRAIN TUMOR DETECTION

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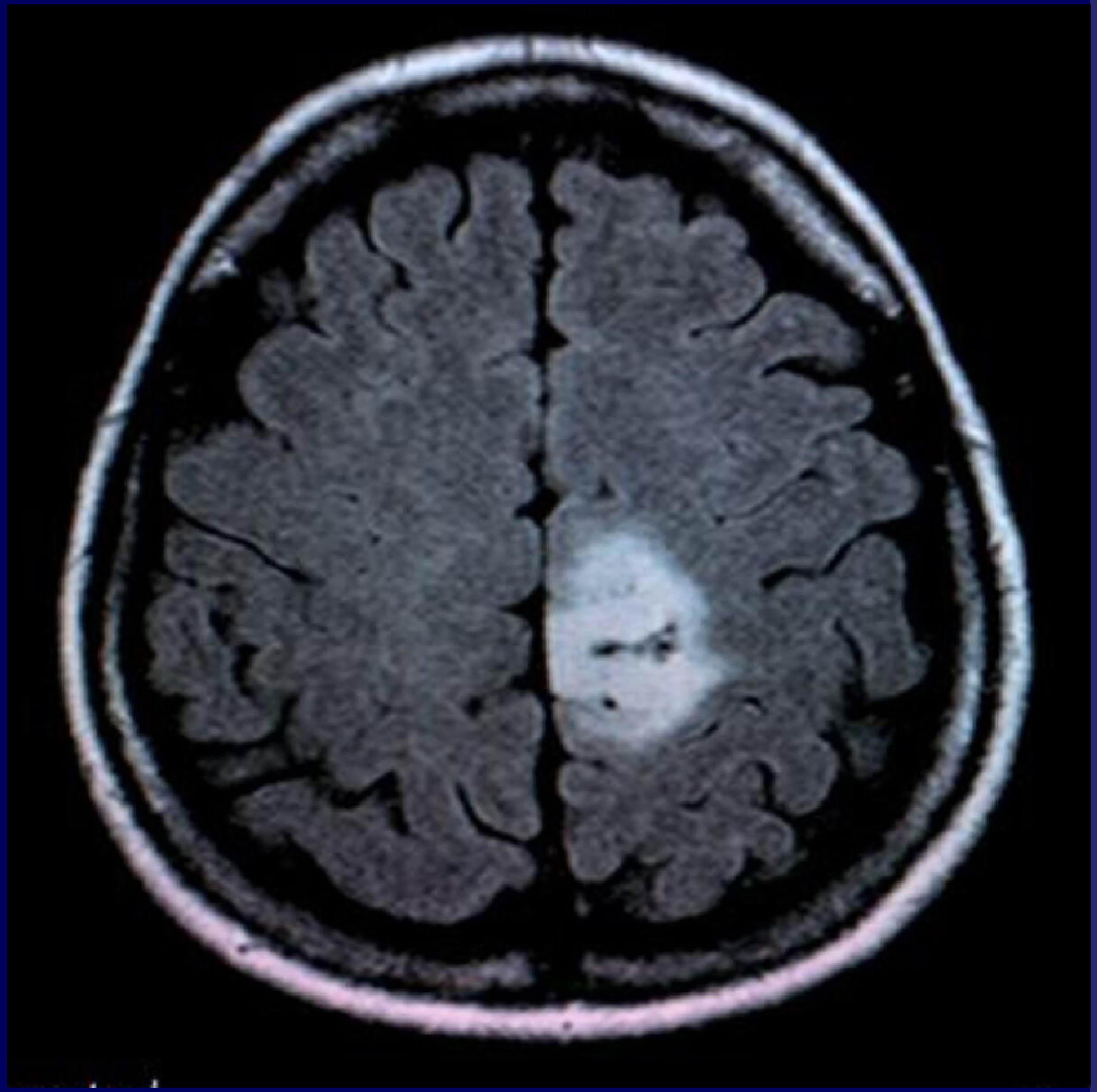
Problem Definition

The human brain, a crucial component of the nervous system, governs daily functions by processing stimuli and coordinating responses.

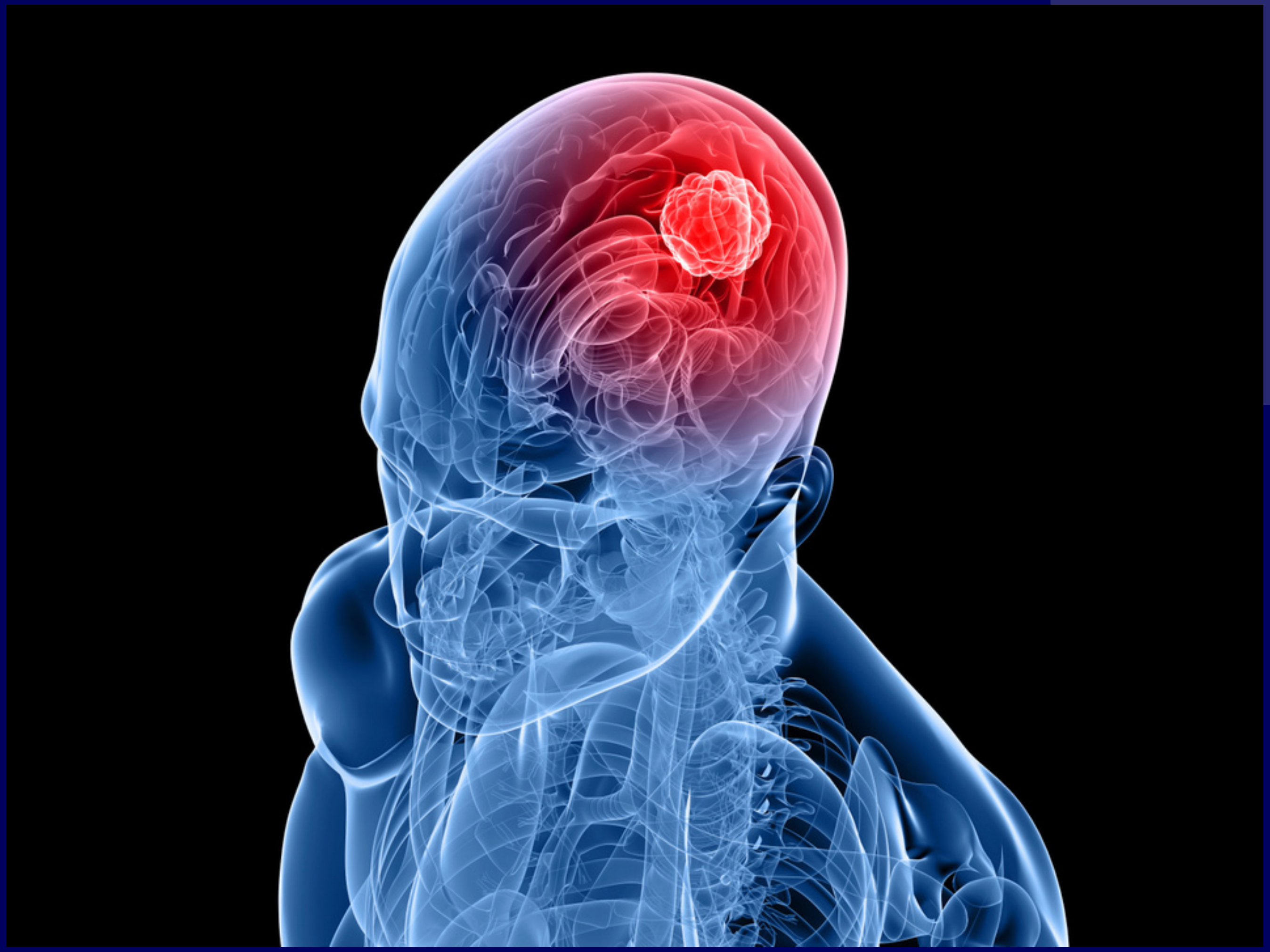
Brain tumors, arising from unchecked cell division, can disrupt normal function and exhibit symptoms such as fatigue, memory issues, and changes in personality. Medical imaging modalities like MRI and CT scans aid radiologists in detecting and classifying brain tumors. Due to its non-invasive nature, MRI is preferred for detailed analysis.

Problem Definition

Manual identification and classification by radiologists are challenging, given variations in tumor characteristics, limited expertise, and the impracticality of handling vast MRI datasets. The study emphasizes the urgent need for a computer-aided diagnostics (CAD) system to enhance brain tumor detection and classification, focusing on both identification and categorization into benign and malignant tumor types.



Related Works



Tiwari P. et al. [1]
Models -> CNN
Dataset -> Brain Tumor Classification (MRI) from Kaggle
Accuracy: 99%

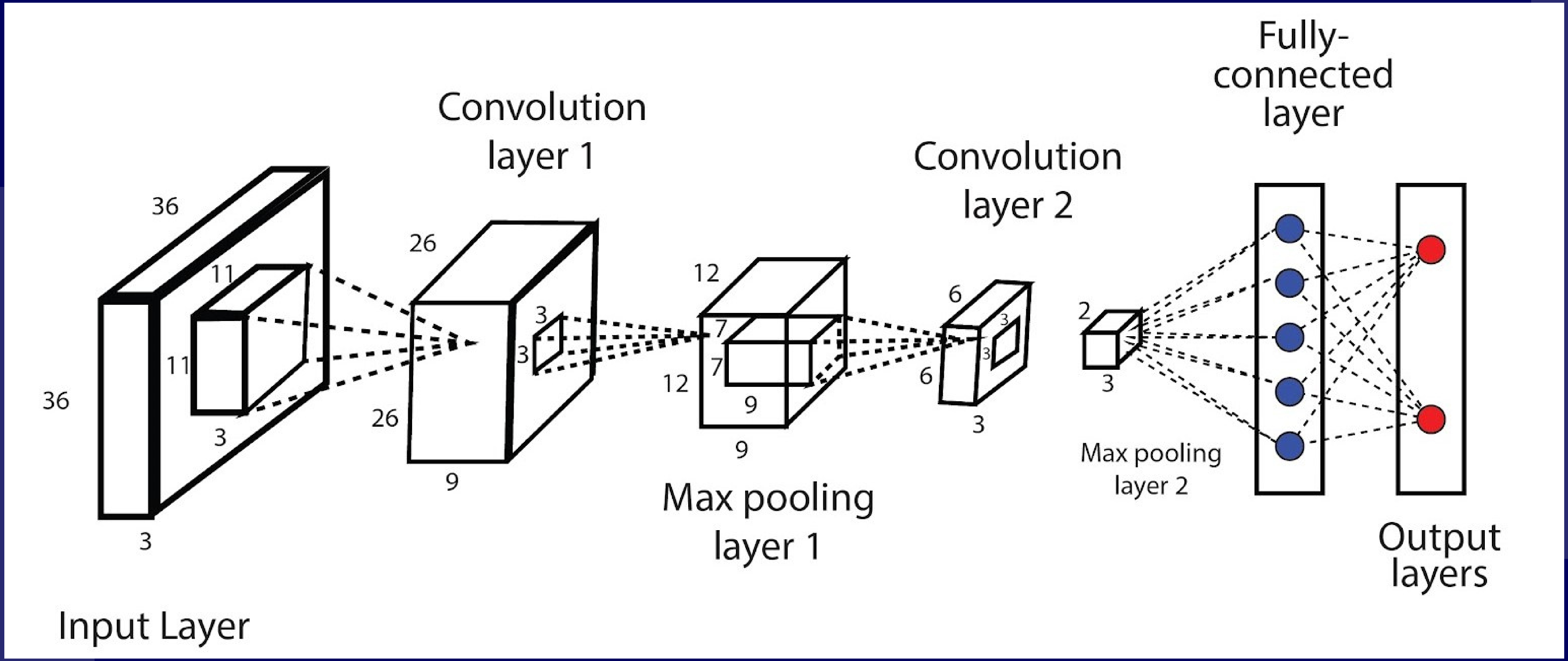
Solanki S. et al. [2]
Models -> LCDEiT
Dataset -> Figshare and BraTS-21 benchmark datasets
Accuracy: 98.11% and 93.68% respectively.

Aulia S. et al. [3]
Models -> VGG-16, CLAHE filter
Dataset -> Cancer Imaging Archive (TCIA) with The Cancer Genome Atlas (TCGA)
Accuracy: 91.08%

Proposal

CNN

Widely used CNN algorithms were utilized for image based data detection.



Dataset

from kaggle

- **shadyeldakrory**/shadyfinal3

	Glioma	Meningioma	Pituitary	no_tumor
Training	4687	4421	4578	1441
Validation	950	900	920	280
Test	950	900	920	280

Pros & Cons

CNN

+ Preserves spatial location for images
+ Deep architectures for detailed images

− Slow learning with 224x224 resolution

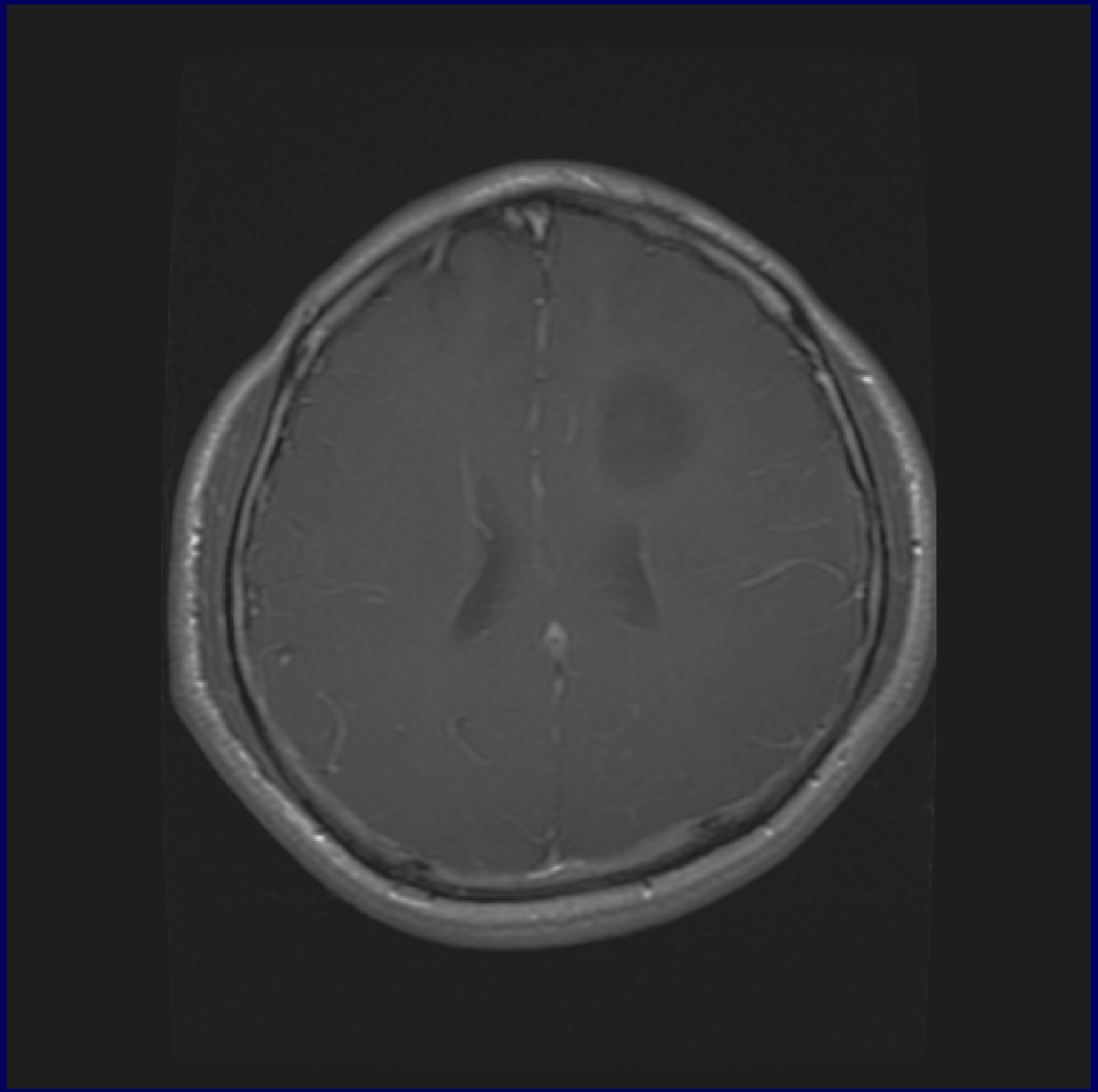
Swin Transformer

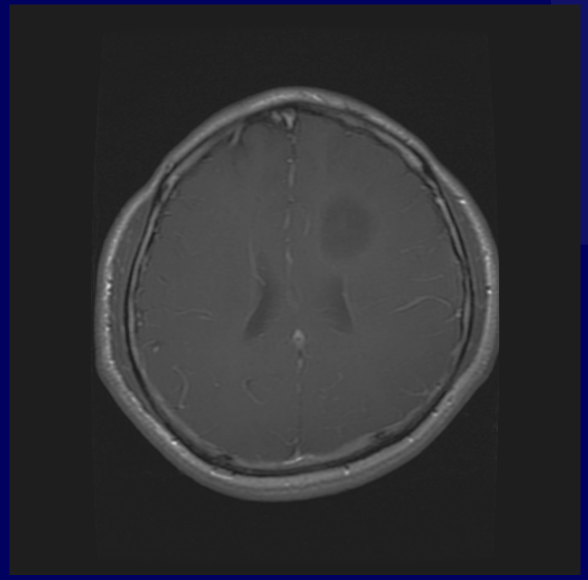
+ Models long-range dependencies
+ Fuses information for multi-modal medical images
+ Robust against removal of layers, easier to modify

− Requires huge amount of data and great computation power

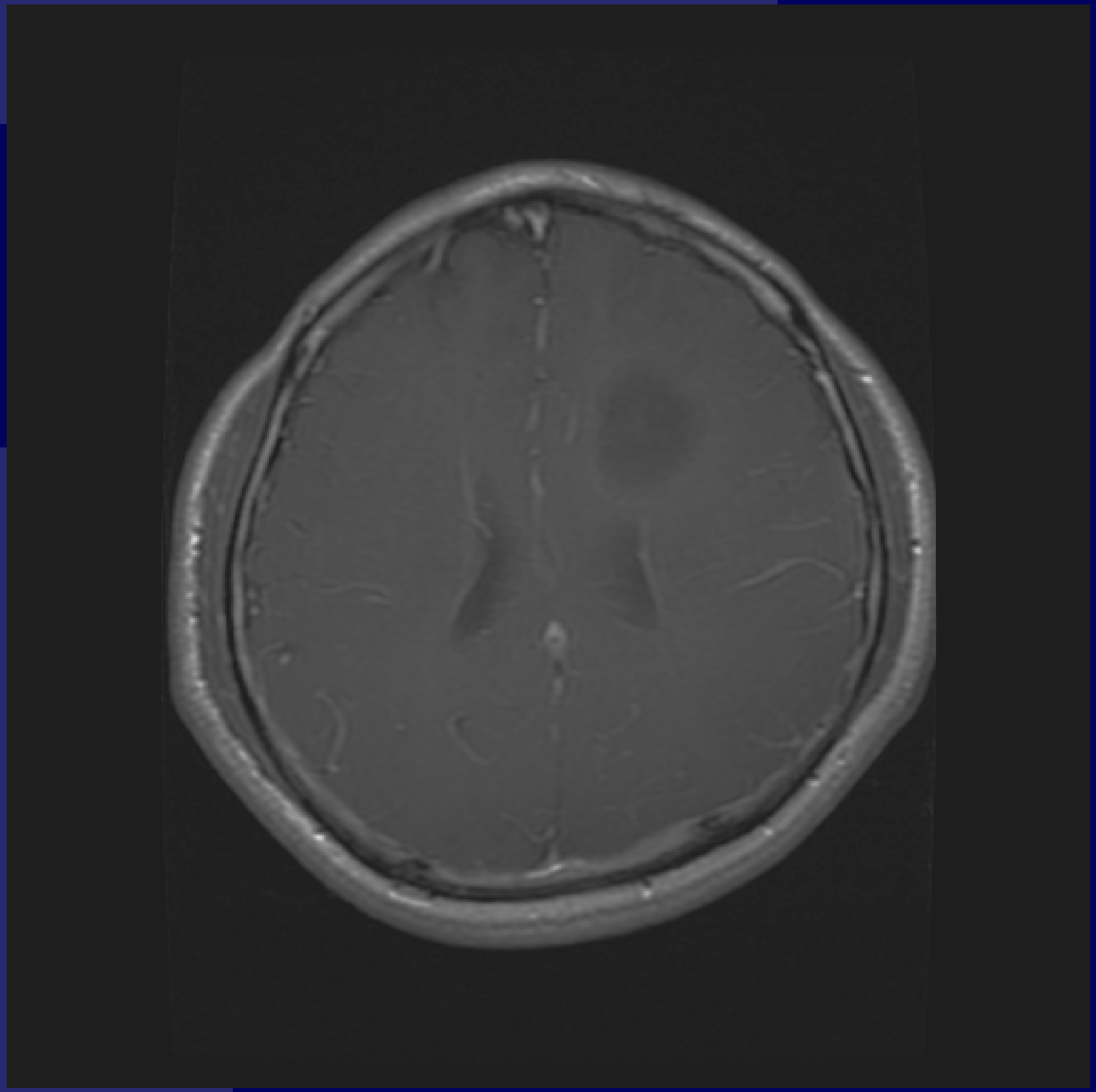
Data Preprocessing

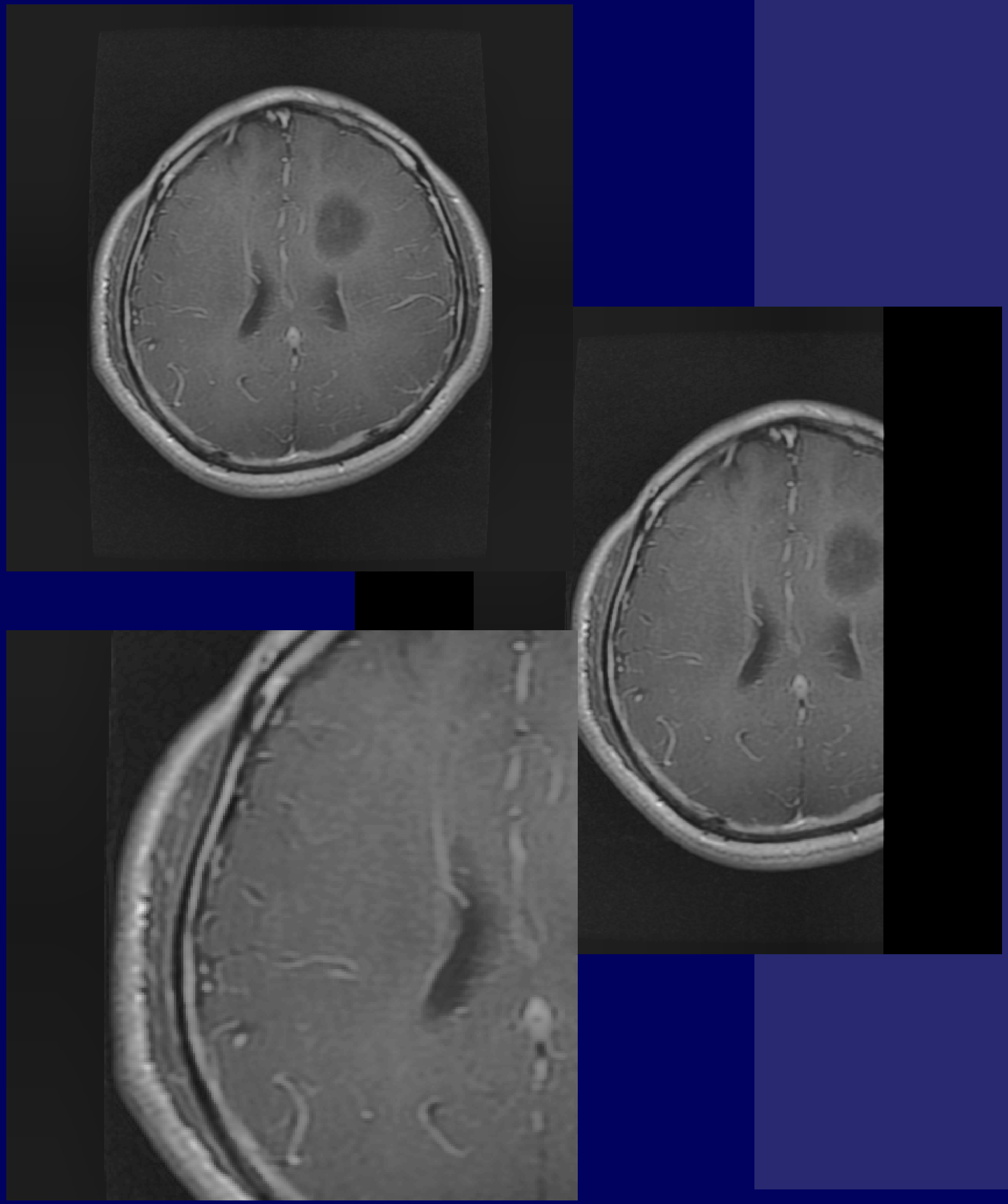
Normalization of data 224x224
Rescaling RGB values [0..1]



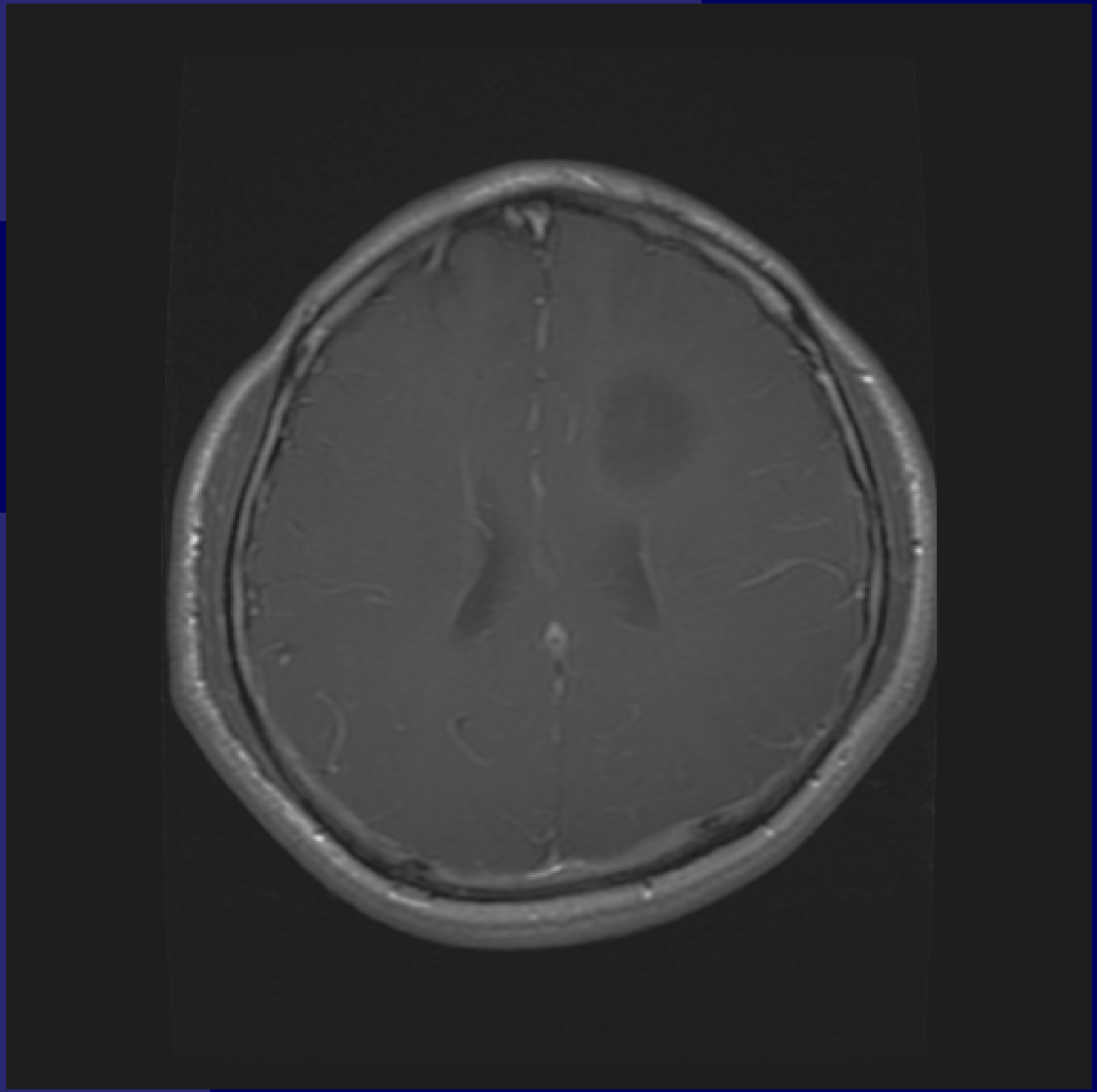


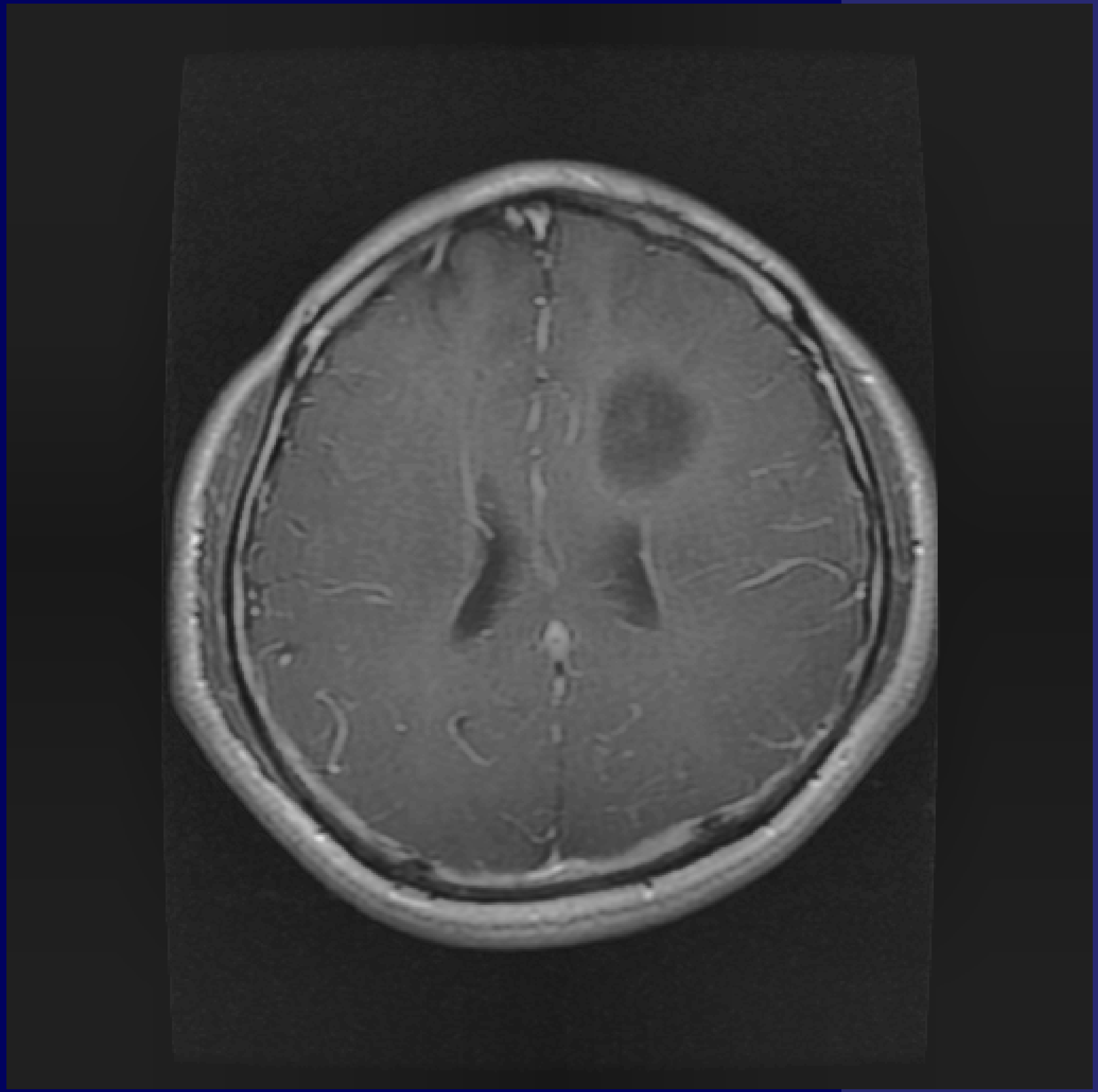
Data Augmentation





CLAHE





Overview of Methods

- ResNet152V2
- ResNet101V2
- ResNet50V2
- DenseNet121
- Xception
- MobileNetV2
- ResNet152V2 + Gaussian noise
- ResNet152V2 + Gaussian noise + CLAHE
- Swin Transformer

Our Method

Softmax

Dense

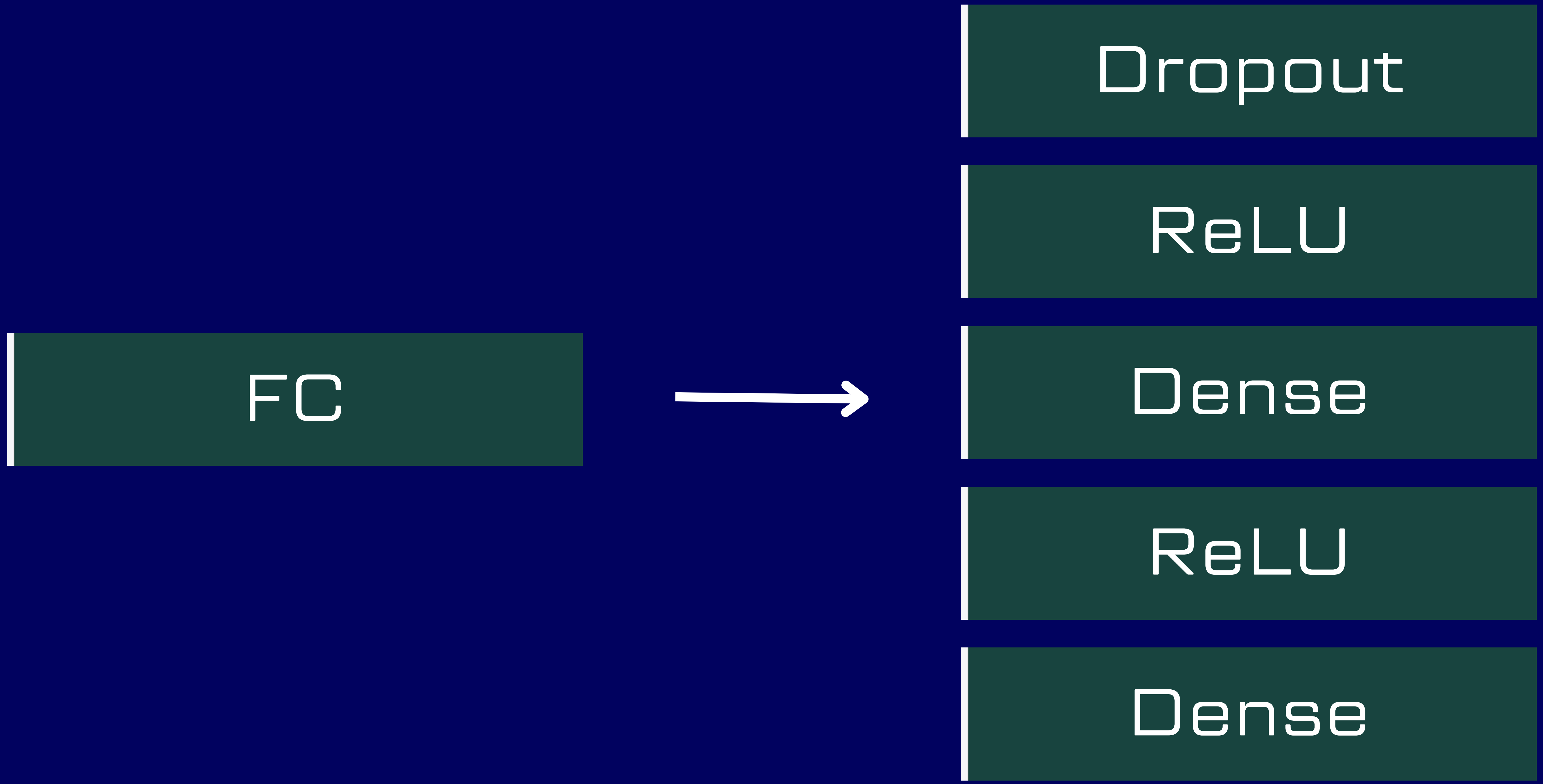
FC

FC

Pool

base
model

Our Method



Our Method

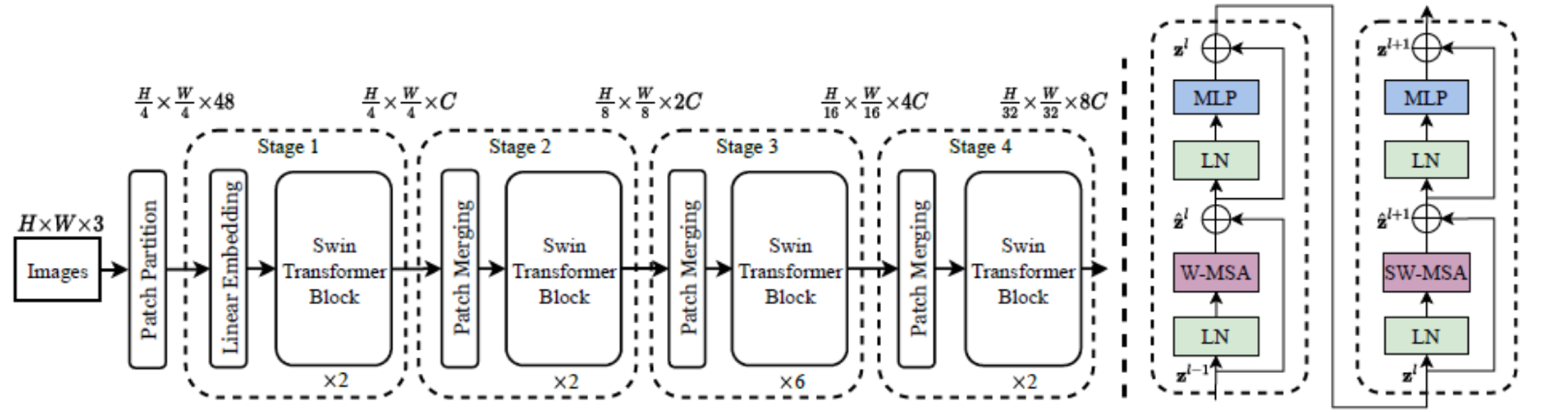
Transfer learning from models trained on ***ImageNet****.*

Frozen basic layers

base
model

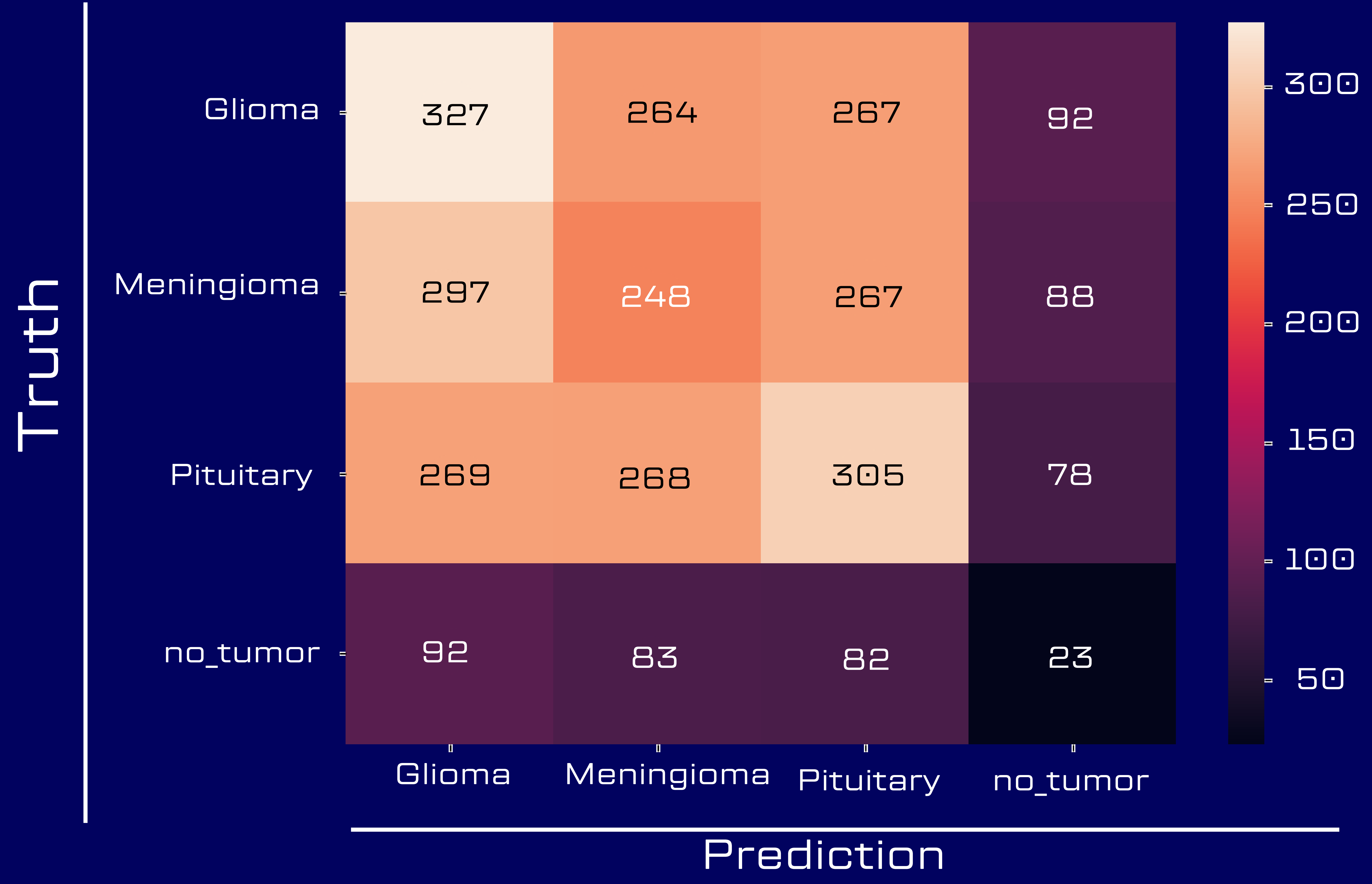
Our Method

- Swin Transformer Model



(a) Architecture (b) Two Successive Swin Transformer Blocks

Experimental Result



Result Table / Training

Model Name	Train Loss	Train Acc	Train Precision	Train Recall	Train F1 Score
SwinTransformer	0.0480	0.9820	0.9850	0.9804	0.9766
Resnet152V2WGNoise	0.1362	0.9417	0.9545	0.9310	0.9154
Resnet152V2WChale	0.0643	0.9758	0.9824	0.9691	0.9668
MobileNetV2	0.0805	0.9717	0.9763	0.9687	0.9595
DenseNet121	0.0572	0.9807	0.9838	0.9783	0.9736
Xception	0.1716	0.9478	0.9580	0.9383	0.9285
ResNet50V2	0.0916	0.9682	0.9730	0.9636	0.9557
ResNet101V2	0.0531	0.9799	0.9832	0.9775	0.9736
ResNet152V2	0.0465	0.9827	0.9858	0.9805	0.9757

Result Table / Validation

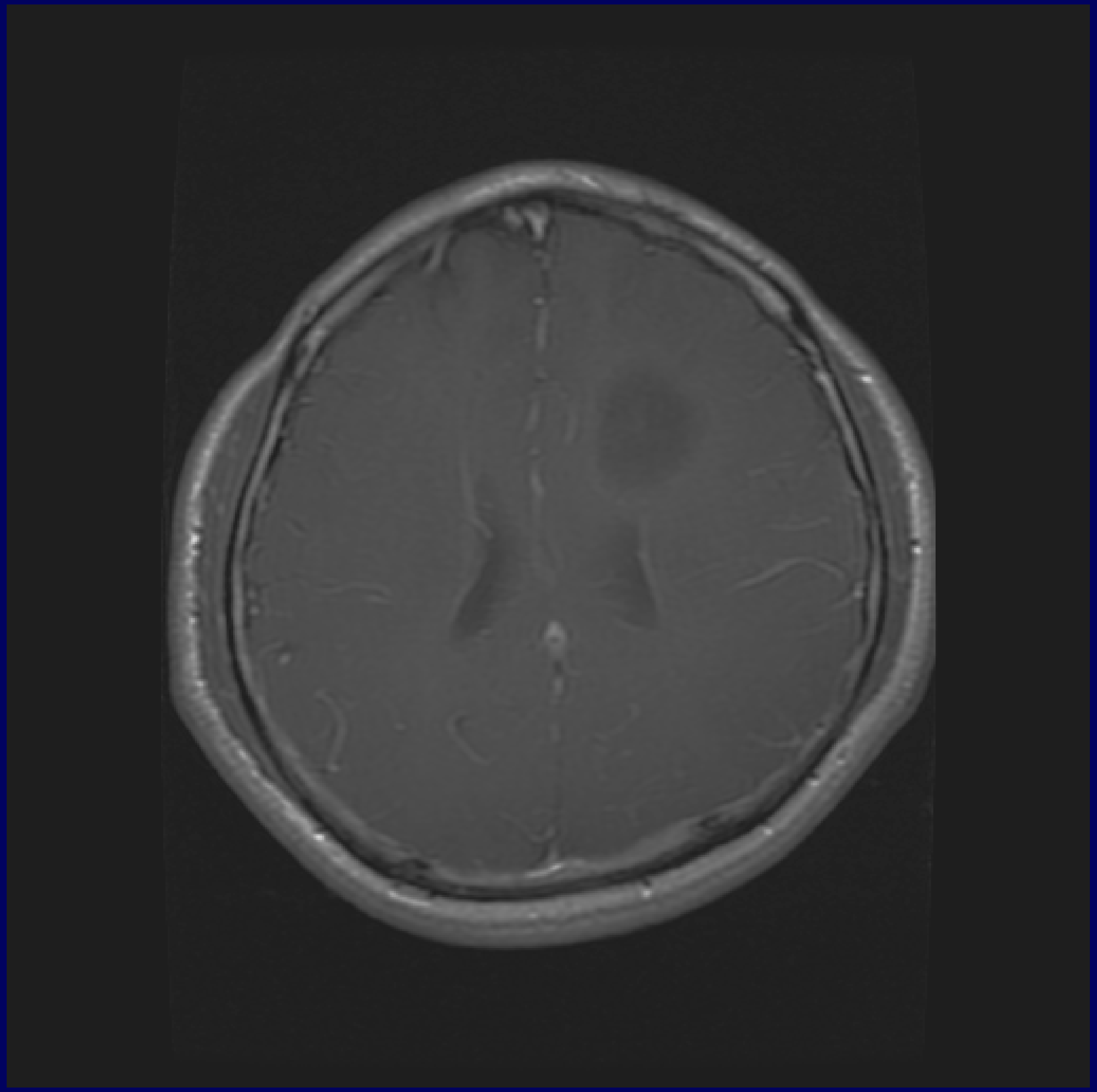
Model Name	Val Loss	Val Acc	Val Precision	Val Recall	Val F1 Score
SwinTransformer	0.3546	0.9111	0.9125	0.9098	0.8378
Resnet152V2WGNoise	0.2526	0.9200	0.9259	0.9134	0.8773
Resnet152V2WChale	0.1498	0.9508	0.9591	0.9449	0.9299
MobileNetV2	0.3617	0.8843	0.8915	0.8810	0.8807
DenseNet121	0.0859	0.9734	0.9734	0.9728	0.9636
Xception	0.2807	0.9184	0.9312	0.8967	0.8936
ResNet50V2	0.1973	0.9374	0.9424	0.9334	0.9220
ResNet101V2	0.1390	0.9590	0.9599	0.9587	0.9440
ResNet152V2	0.0905	0.9711	0.9724	0.9708	0.9604

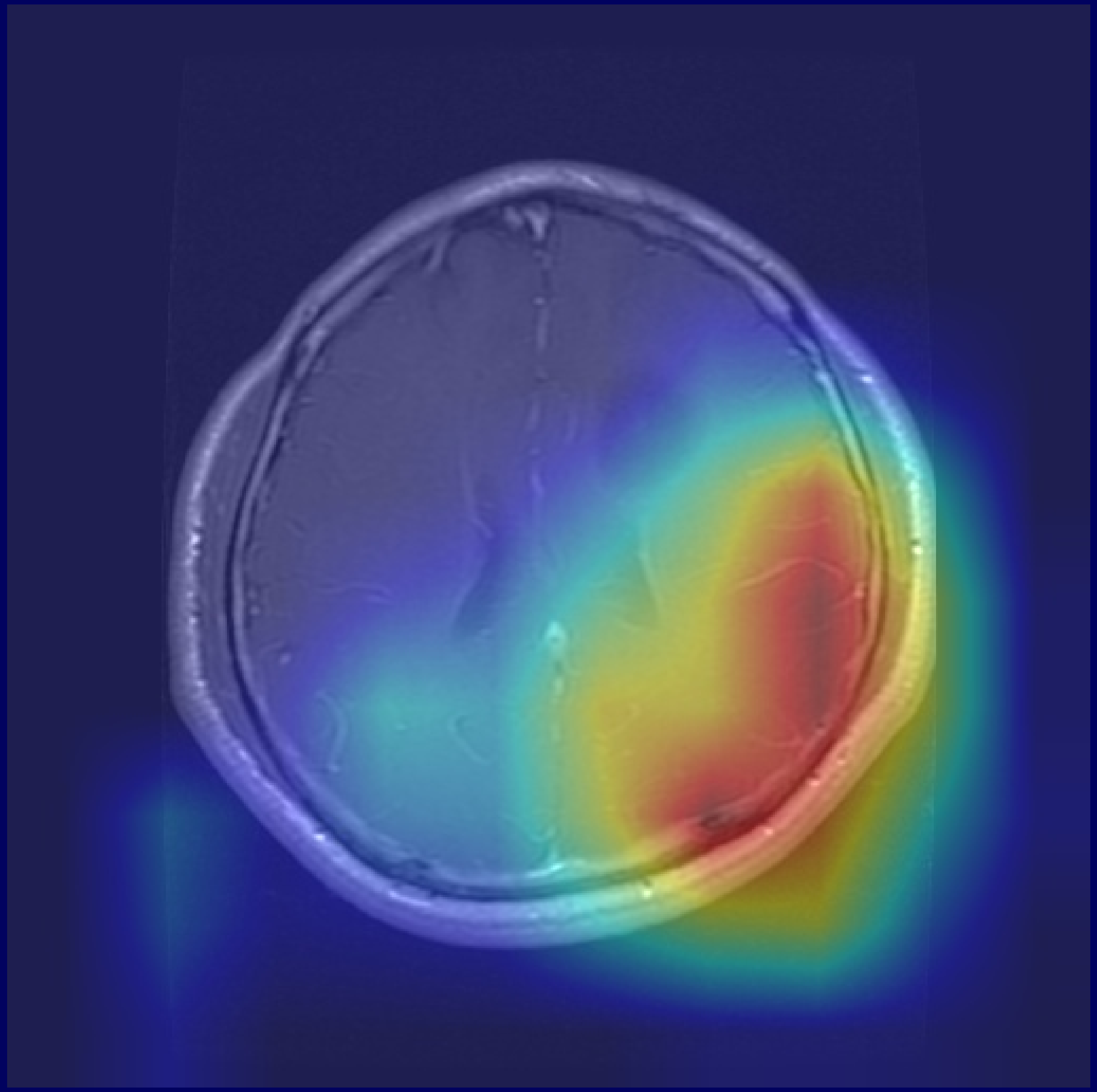
Result Table / Test

Model Name	Test Loss	Test Acc	Test Precision	Test Recall	Test F1 Score
SwinTransformer	0.4619	0.8954	0.8976	0.8938	0.8145
Resnet152V2WGNoise	0.3225	0.8987	0.9039	0.8915	0.8381
Resnet152V2WChale	0.2124	0.9439	0.9474	0.9387	0.9122
MobileNetV2	0.4298	0.8561	0.8739	0.8433	0.8173
DenseNet121	0.3907	0.8895	0.8895	0.8836	0.8054
Xception	0.3734	0.8830	0.8918	0.8725	0.8100
ResNet50V2	0.2227	0.9285	0.9325	0.9239	0.9065
ResNet101V2	0.2316	0.9439	0.9448	0.9433	0.9250
ResNet152V2	0.1020	0.9718	0.9731	0.9708	0.9561

Data Visualization

Grad-Cam





Contribution

Bekir Emirhan Akay	Fatih Yalçın	Murat Tatlı	Mehmet Alpay
ResNet models with Noise and CLAHE	CNN architectures	Transformer model	CNN architectures
Methodology	Related Work	Introduction	Conclusion
Future Works	Future Works	Theory	Experiment Result

References

[1] Tiwari, P., Pant, B., Elarabawy, M. M., Abd-Elnaby, M., Mohd, N., Dhiman, G., & Sharma, S. (2022). Cnn based multiclass brain tumor detection using medical imaging. Computational Intelligence and Neuroscience, 2022.

[2] Ferdous, G. J., Sathi, K. A., Hossain, M. A., Hoque, M. M., & Dewan, M. A. A. (2023). LCDEiT: A Linear Complexity Data-Efficient Image Transformer for MRI Brain Tumor Classification. IEEE Access, 11, 20337-20350.

[3] Aulia, S., & Rahmat, D. (2022). Brain Tumor Identification Based on VGG-16 Architecture and CLAHE Method. JOIV: International Journal on Informatics Visualization, 6(1), 96-102.

Thanks!

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