東北大学
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Brain tumor detection on MRI using a CNN

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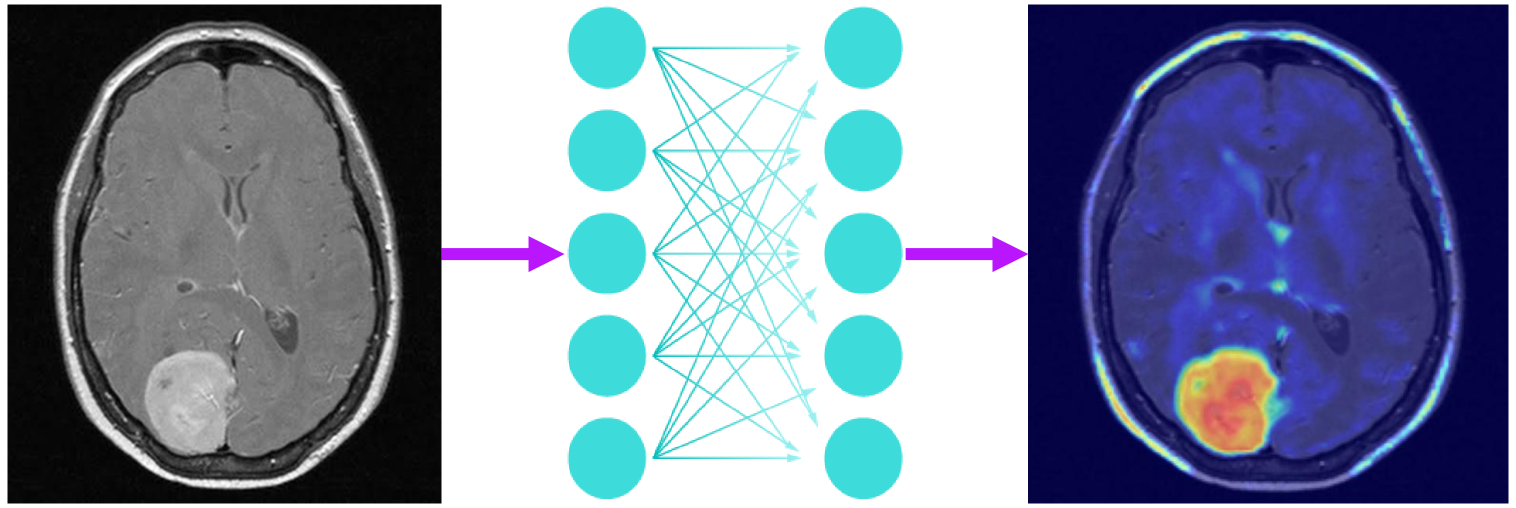
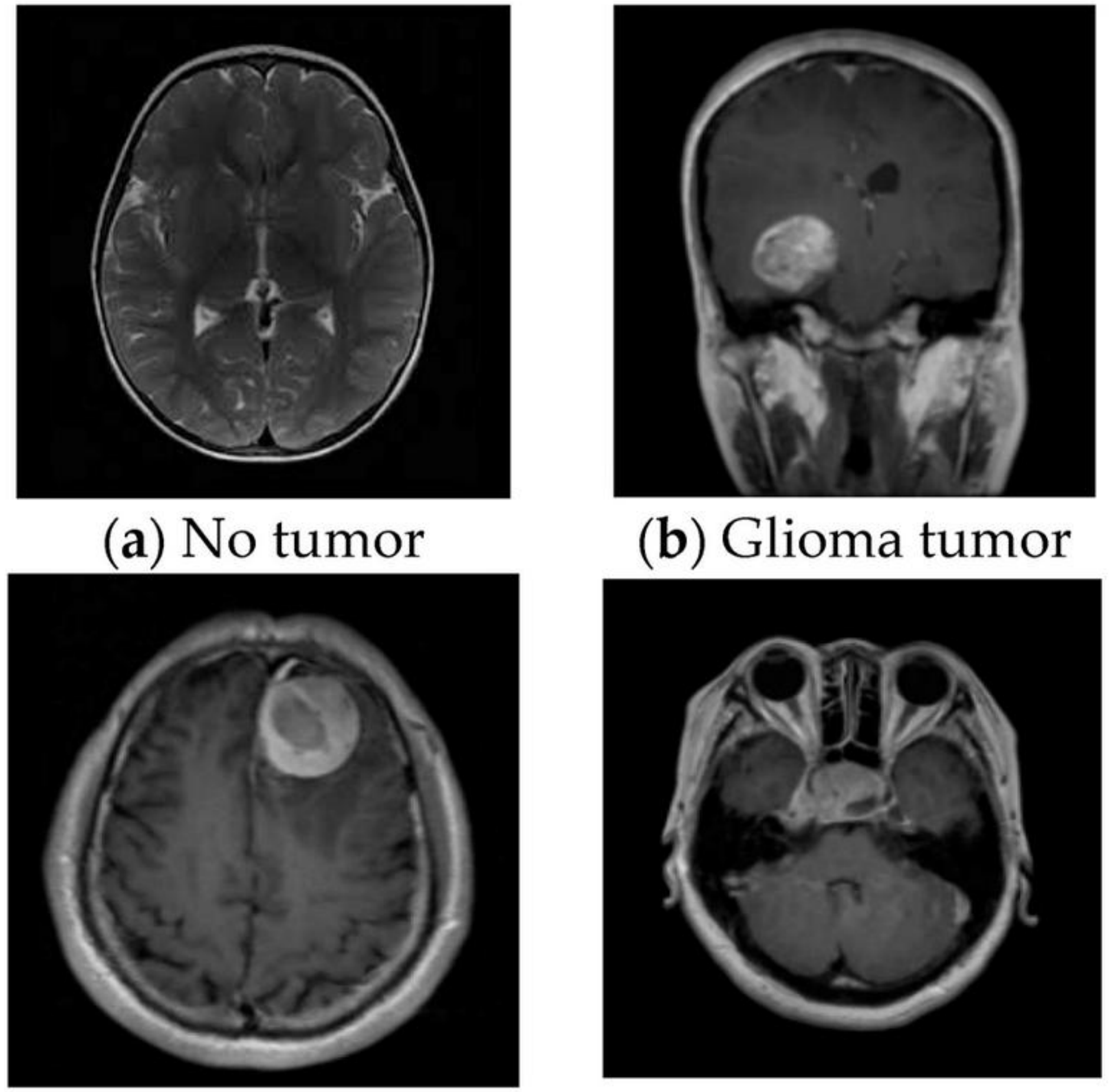
Background



- **Previous work**:
  - BrainMRI Tumor Classifier Pytorch on GitHub
  - Deep Learning in Medical Image Classification from MRI-based Brain Tumor Images by Xiaoyi Liu & Zhuoyue Wang

- **Goal**:
  - Comparaison of different model for MRI head tumor detection



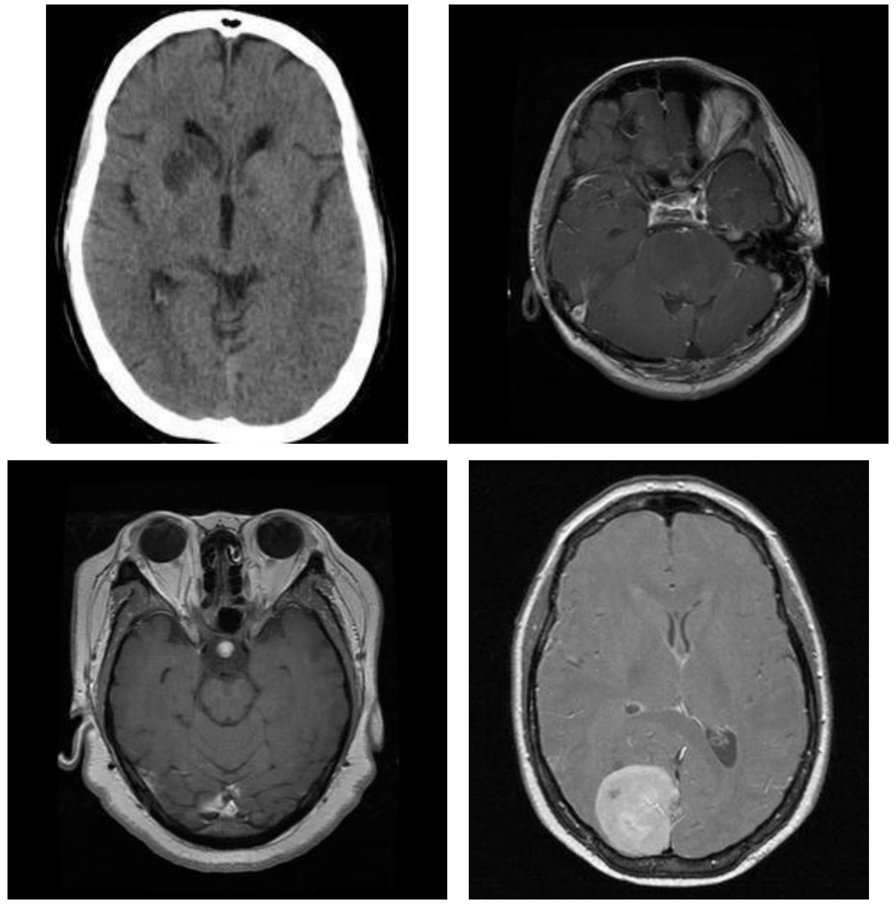
(a) No tumor (b) Glioma tumor (c) Meningioma tumor (d) Pituitary tumor

Dataset

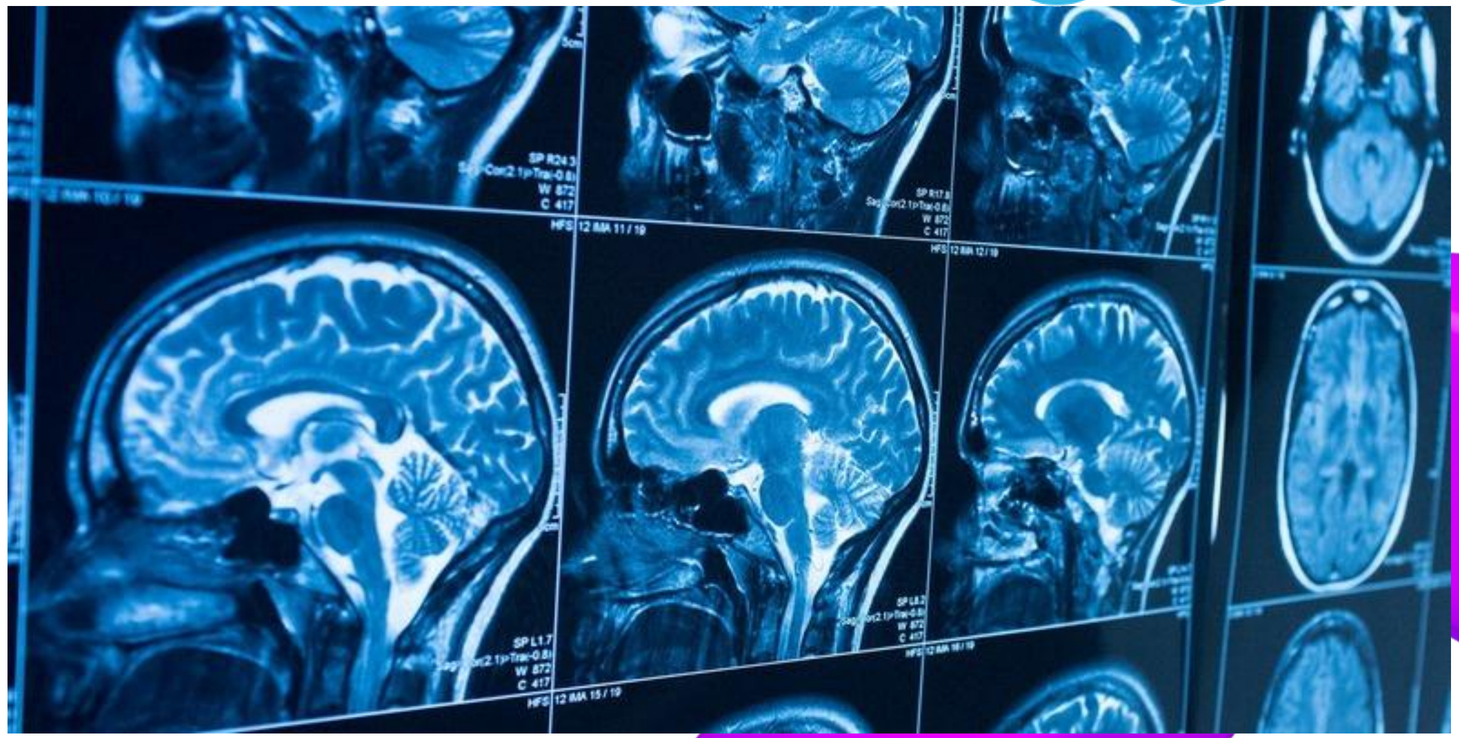
Brain Tumor MRI Dataset by Masoud Nickparvar

Training :
- Glioma: **300 pictures**
- Meningioma: **306 pictures**
- No tumor: **405 pictures**
- Pituitary: **300 pictures**

Testing:
- Glioma**: 1321 pictures**
- Meningioma**: 1339 pictures**
- No tumor**: 1595 pictures**
- Pituitary**: 1457 pictures**



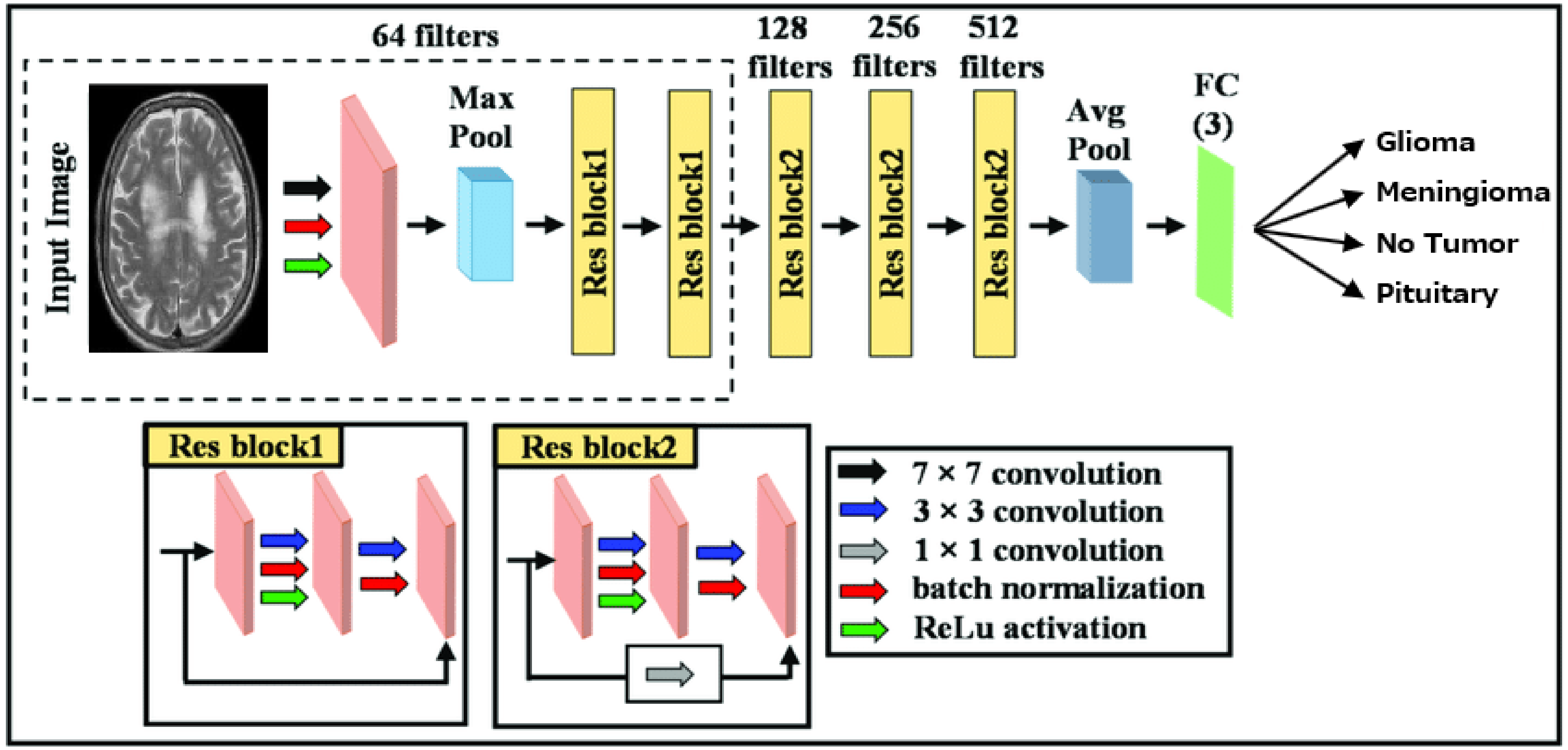
kaggle



https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset

Methodology

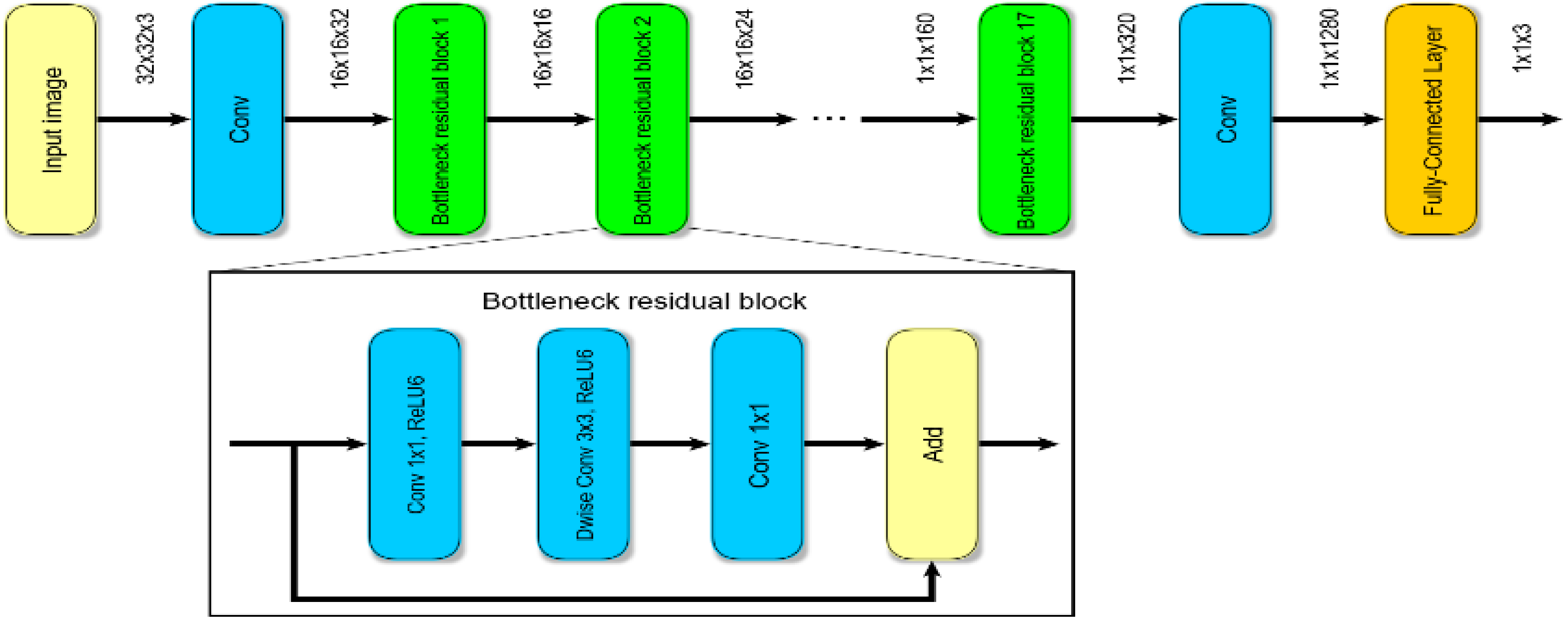
ResNet-18



- **Simple Residual Blocks:** ResNet-18 relies on residual blocks with skip connections to bypass nonlinear layers. Each block performs a transformation and adds the input directly to the output.
- **Moderate Depth:** Includes 18 convolutional layers structured into 4 main blocks. Moderate depth maintains low complexity while leveraging the benefits of a deep network.
- **Progressive Downsampling:** The network reduces spatial resolution progressively through stride 2 convolutions and Max Pooling layers. Extracts global features while reducing data dimensions.

Methodology

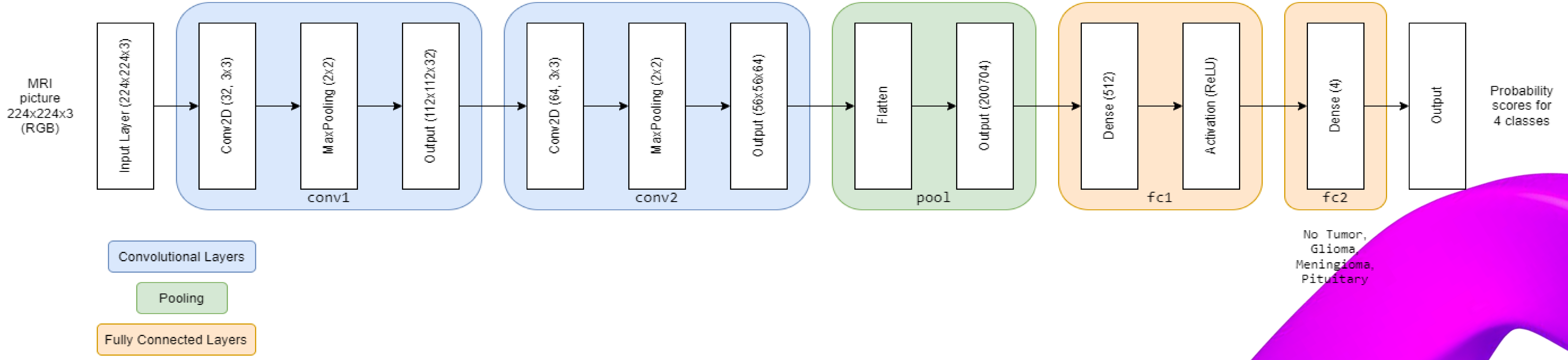
MobileNet-v2



- **Inverted Residuals Blocks:** Each block starts with an expansion of the input channels dimensions (via a 1×1 convolution). Follows a Depthwise Separable Convolution to capture features without exploding computations. Finally, it compresses the dimensions to reduce memory costs.
- **Depthwise Separable Convolution:** Depthwise Convolution (applied separately on each channel) & Pointwise Convolution (combines channels). Drastically reduces parameters and computations while maintaining performance.
- **Memory optimization strategy:** MobileNet-v2 uses limited activations (ReLU6) and a compact structure to facilitate quantization. Optimized for mobile or embedded devices, with a small memory footprint

Methodology

BrainTumorNet



- **<u>Sequential structure with Convolution + Pooling blocks:</u>** Two convolutional blocks allow to extract local features while progressively reducing the spatial dimensions. Each convolutional layer increases the depth of the features to capture increasingly complex information.
- **<u>Transition to dense layers via Flatten:</u>** After convolutions and pooling, the features are flattened into a 1D vector. Fully connected layers allow to combine the global information to produce a classification or prediction.
- **<u>Use of a ReLU activation for non-linearity:</u>** A ReLU activation function is used in the intermediate dense layer to introduce non-linearity. The last dense layer is designed for 4-class classification.

Results

Recall	Brain Tumor MRI Dataset by Masoud Nickparvar
Resnet-18	97,47%
MobileNet-v2	97,15%
BrainTumorNet	98,89%

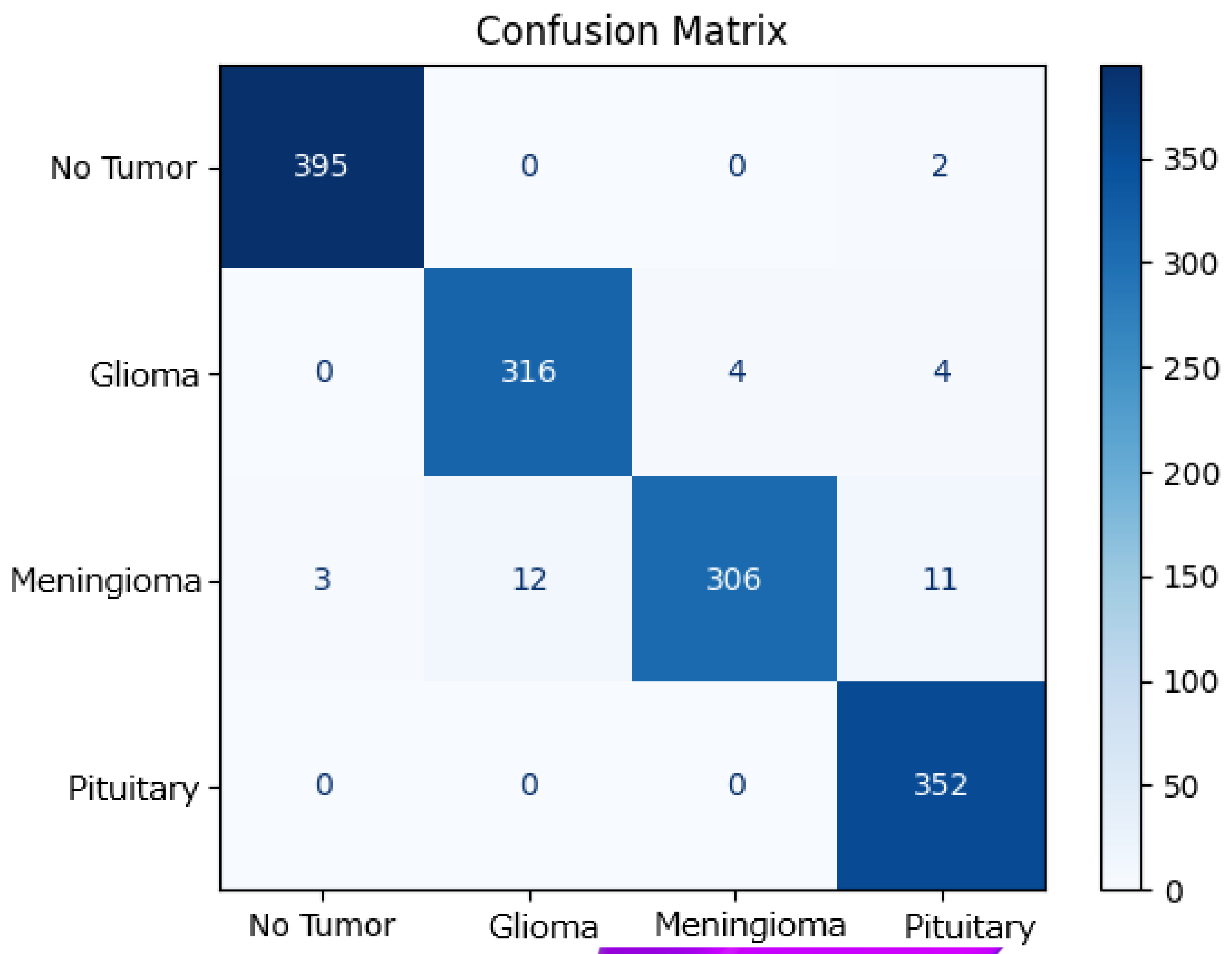
Precision	Brain Tumor MRI Dataset by Masoud Nickparvar
Resnet-18	97,44%
MobileNet-v2	97,65%
BrainTumorNet	98,86%

Hmean	Brain Tumor MRI Dataset by Masoud Nickparvar
Resnet-18	97,46%
MobileNet-v2	97,39%
BrainTumorNet	98,88%

Results

ResNet-18

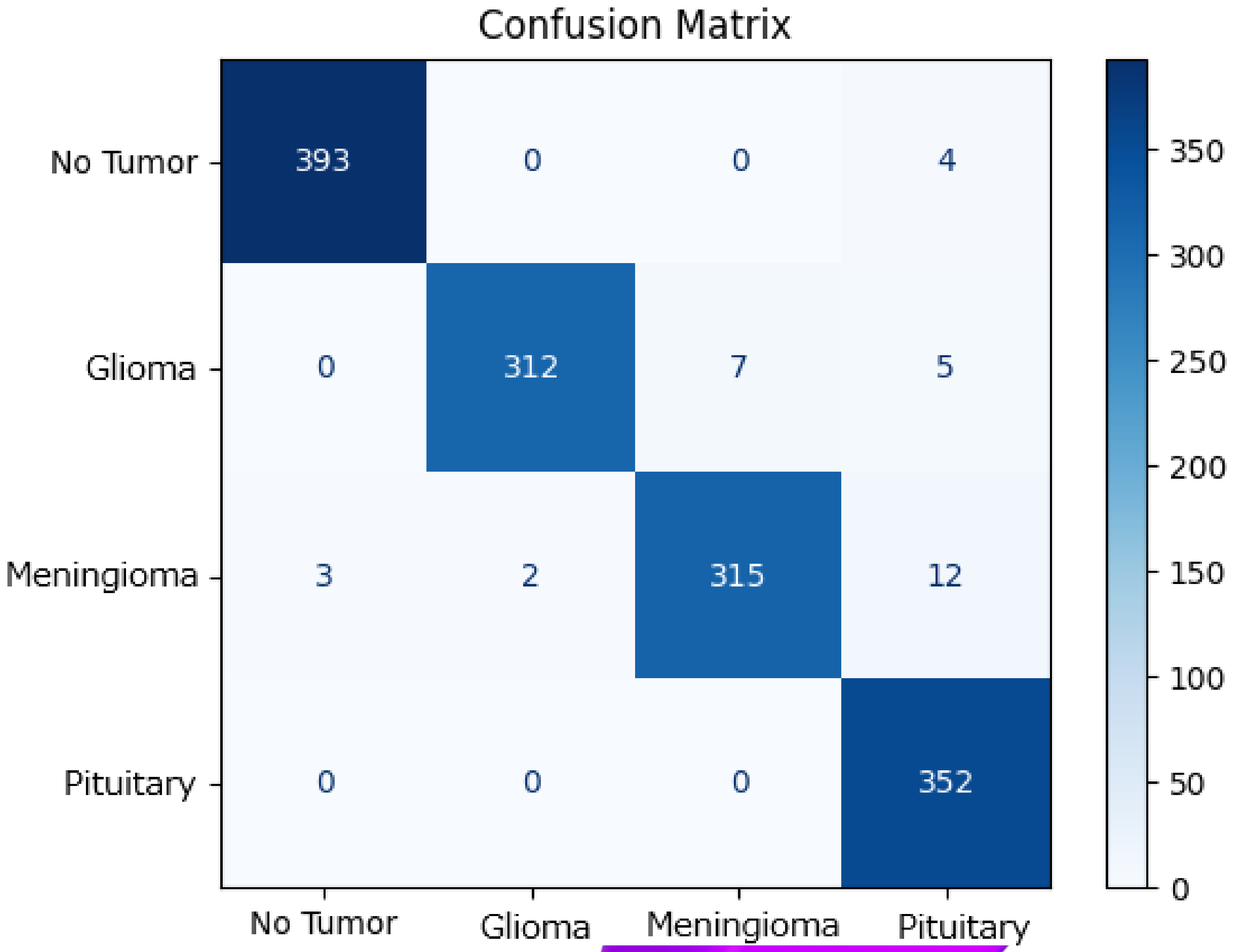
- **<u>Classes with the best performances:</u>**
  - "No Tumor" and "Pituitary" are perfectly handled with near perfect precision and recall. This shows that the model is very reliable in detecting these two categories.
- **<u>Class with average performance:</u>**
  - "Meningioma" shows a slight weakness, with some confusions with other classes. These errors could be due to visual similarity or close features of other tumor types in the images.
- **<u>Class well handled:</u>**
  - "Glioma" is well handled, with a very low error rate.



Results

MobileNet-v2

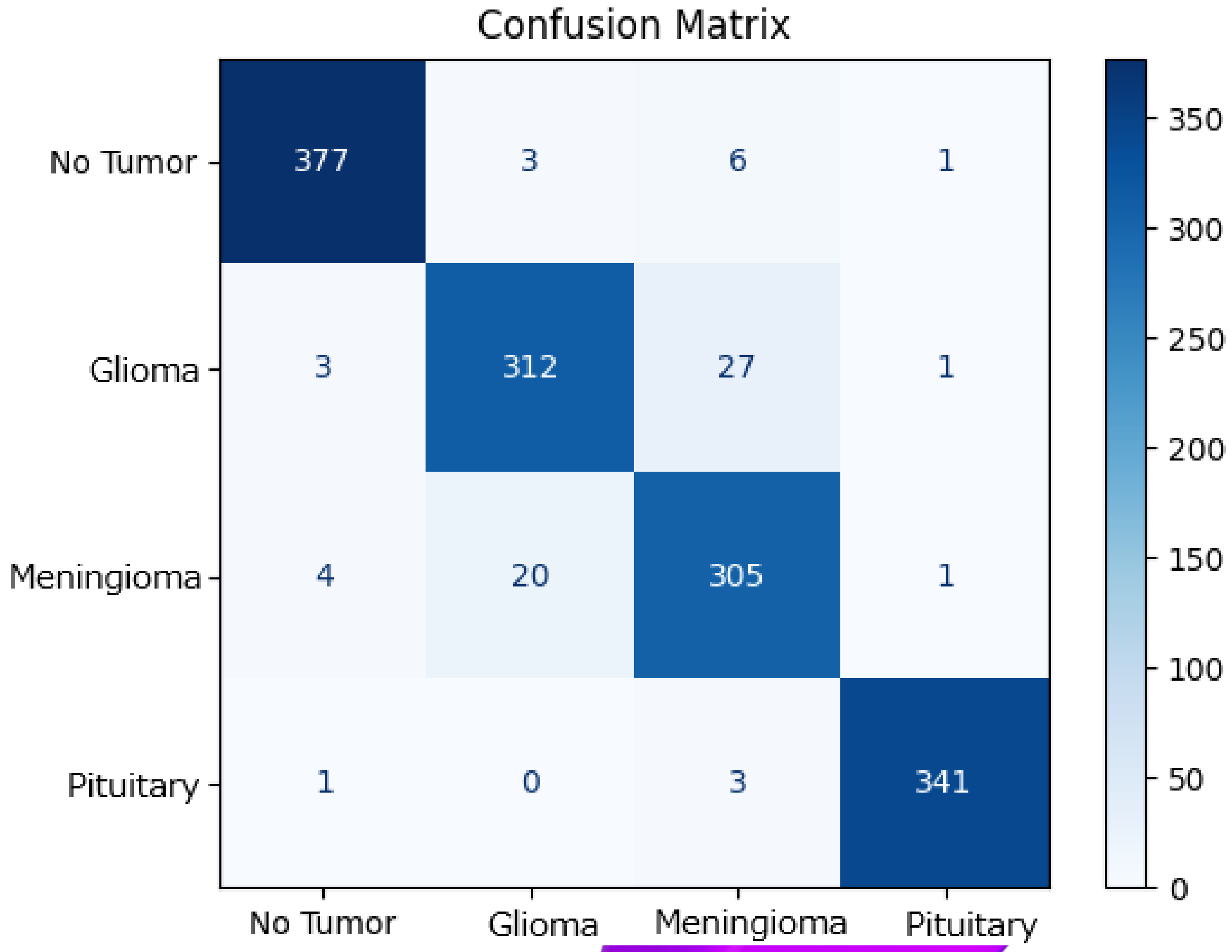
- **Classes with the best performance:**
  - "No Tumor" and "Pituitary" continue to be handled perfectly or almost perfectly.
- **Class with a slight improvement:**
  - "Meningioma" is better handled, with a reduction in false negatives compared to ResNet-18. This could be due to better features extracted by this model.
- **Class with relative weaknesses:**
  - "Glioma" shows slightly worse performance than ResNet-18, with a slightly higher false negative and false positive rate.



Results

BrainTumorNet

- **<u>Classes with strong performance:</u>**
  - "Pituitary" is handled with high accuracy and low error rates.
  - "No Tumor" is also handled well despite a slight increase in false negatives.
- **<u>Classes requiring improvement:</u>**
  - "Glioma" and "Meningioma" show more pronounced difficulties, with a higher rate of false negatives. This may indicate that some shared features between these two classes cause confusion.



Conclusion

- **<u>ResNet-18</u>**: Most stable model with good overall balance between precision and recall. Reliable performance on all classes, especially for "No Tumor" and "Pituitary".

- **<u>MobileNet-v2</u>**: Offering slightly better precision and good recall, especially effective for complex classes like "Meningioma". A solid trade-off for overall performance.

- **<u>BrainTumorNet</u>**: Best overall performance thanks to exceptional precision and recall. Some challenges remain to improve the treatment of complex cases ("Glioma" and "Meningioma").

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Thank you for your attention

https://github.com/Zouzzou21/Tohoku-University-Courses/tree/main/COLABS

References

- **ResNet-18**:
  - Picture
  - https://pytorch.org/hub/pytorch_vision_resnet/
- **MobileNet-v2**:
  - Picture
  - https://pytorch.org/hub/pytorch_vision_mobilenet_v2/

- **DataSet:**
  - https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset

- **Research Paper**
  - https://github.com/HalemoGPA/BrainMRI-Tumor-Classifier-Pytorch
  - https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2019.00810/full
  - https://ar5iv.labs.arxiv.org/html/2408.00636
  - https://bmcmedinformdecismak.biomedcentral.com/articles/10.1186/s12911-023-02114-6
  - https://pubmed.ncbi.nlm.nih.gov/38223737/