BRAIN TUMOR CLASSIFICATION

OUTLINE

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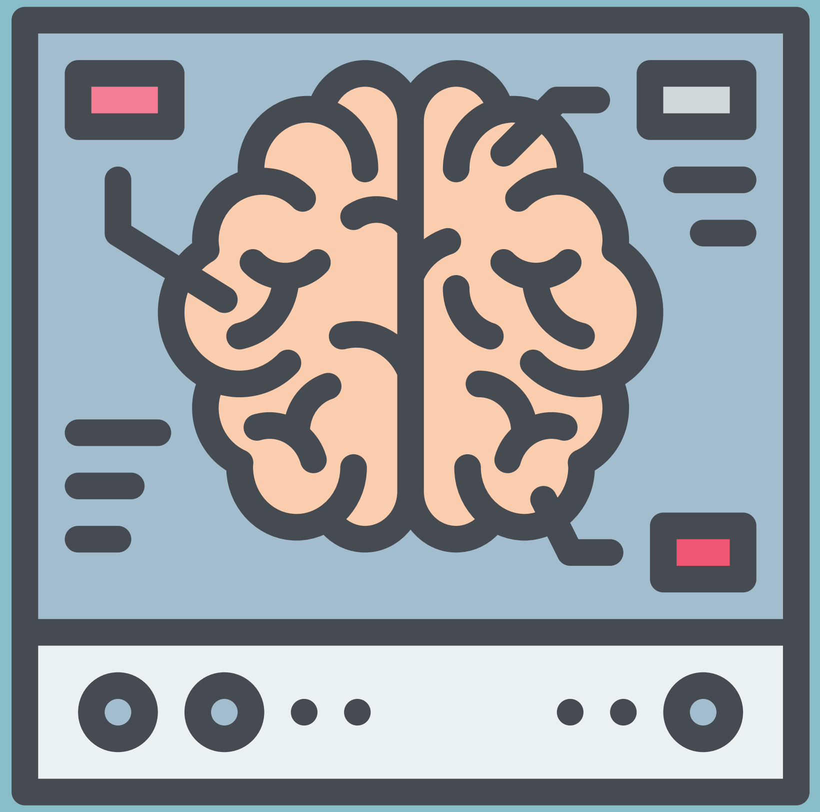
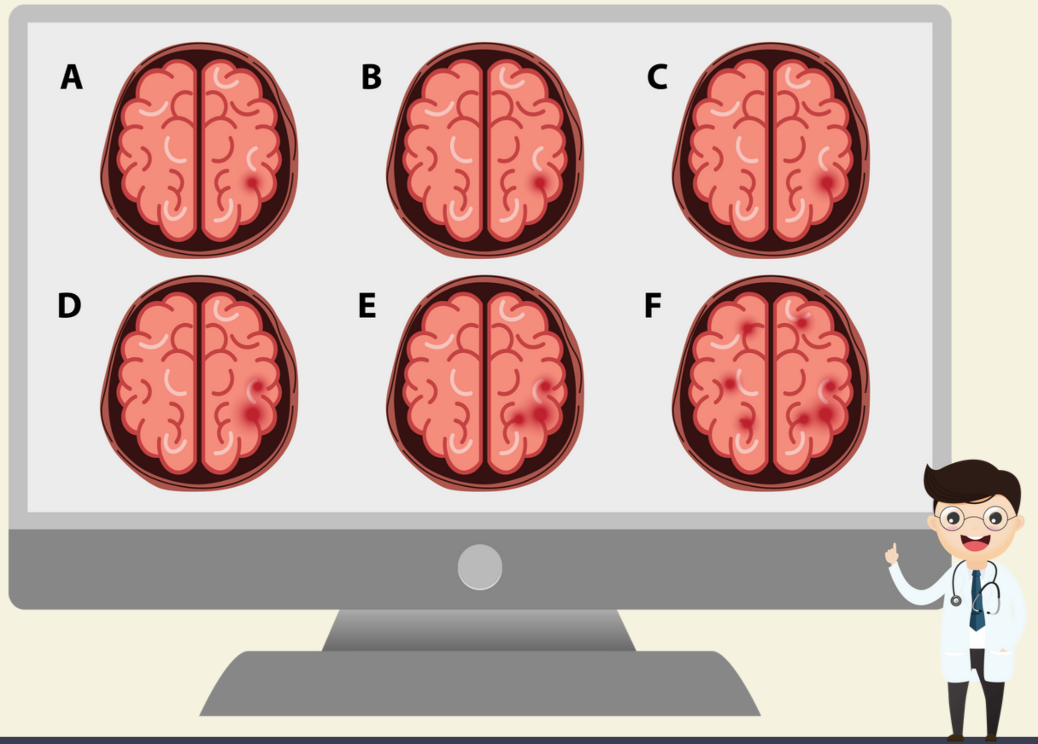


What is brain tumor classification? 🤔

Brain tumor classification refers to the process of categorizing brain tumors into different types or sub types based on their characterisitcs, such as histological features, genetic markers, imaging data and clinical information.



COMPELLING ATTRIBUTES

- We have used TensorFlow: An open-source machine learning framework developed by Google to strengthen the precision and efficiency of brain tumor diagnosis.
- Addition to precision and efficiency Tensorflow has various advantages:
    - Transfer learning
    - Visualisation and interpretability
    - Deployment flexibility

- This project also aims to demonstrate the merging of machine learning, highlighting how artificial intelligence has the potential to transform the healthcare industry.

MOTIVATION

- Our brain tumor classification project is motivated by a strong desire to enhance medical diagnosis and advance the level of patient care.
- Given the significant risks and potential life-threatening consequences posed by brain tumors, early detection is critical to improving treatment success and patient outcomes.

RELATED WORK

In Cheng's study titled "Enhanced Performance of Brain Tumor Classification via Tumor Region Augmemntation and Partition", a compelling approach to brain tumor classification is introduced.

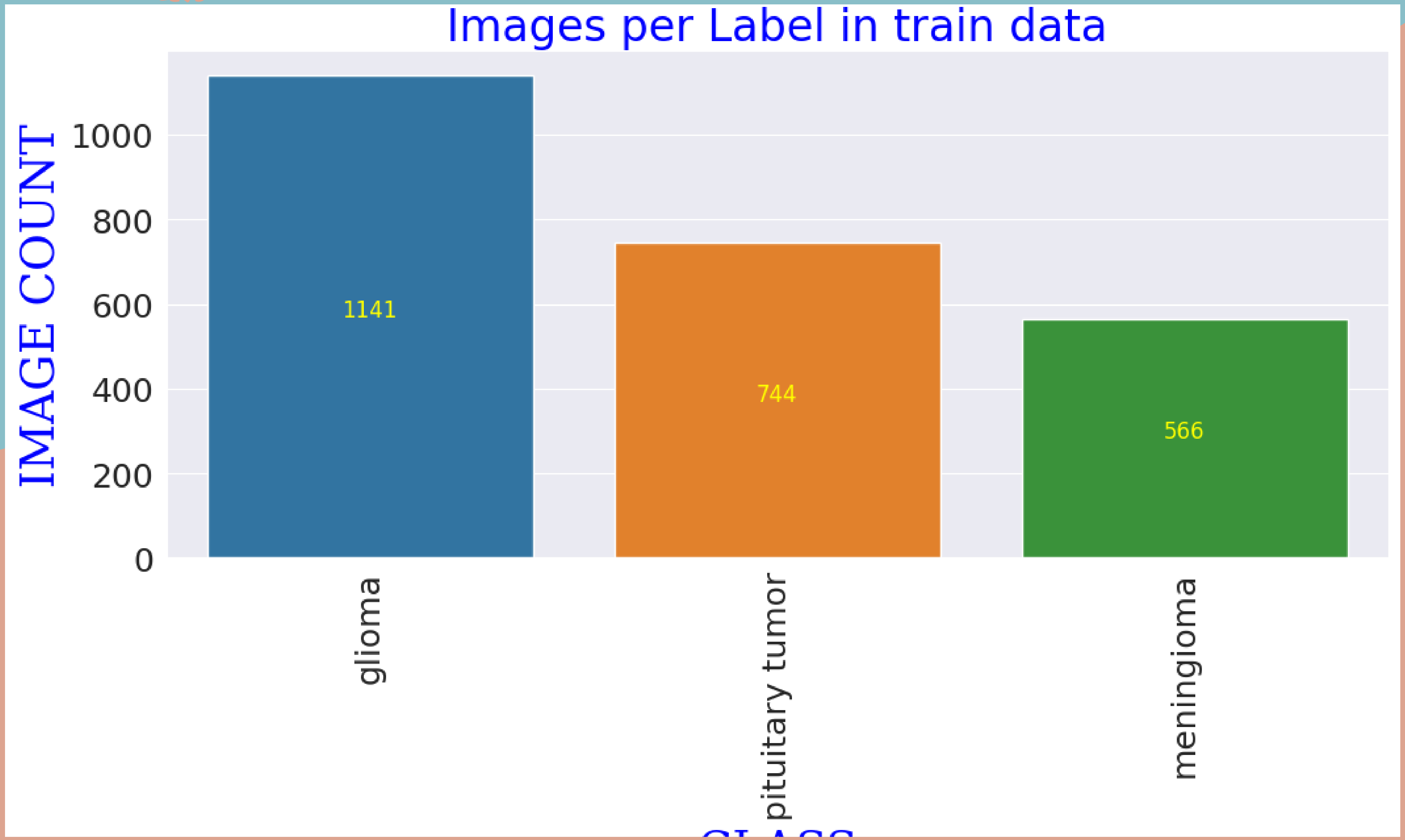
1. The researchers focus on augmenting the tumor region within brain images, enhancing its visibility and distinctiveness for improved accuracy in medical image analysis

2. They further partition the augmented tumor region into smaller segments, enabling a more detailed analysis of the tumor's internal structure, heterogeneity, and spatial distribution.

3. This approach aims to provide valuable insights into the tumor's characteristics, such as shape, texture, and intensity variations, leading to enhanced tumor detection, characterization and ultimately improving outcomes in oncology.

The dataset consists of brain tumor images categorized into meningioma, glioma, and pituitary tumor classes.

ABOUT THE DATASET



*The dataset consists of **3064** slices, with the following distribution among the tumor types:*

*Meningioma: **708** slices*
*Glioma: **1426** slices*
*Pituitary Tumor: **930** slices*

Data Splits

- ***80%** of the data is used for training*
- ***10%** of the data is used for validation*
- ***10%** of the data is used for testing*

PROPOSED WORK

- Used a custom function to load and split the dataset into training, validation, and test sets.
- Augmenting data to increase the diversity of the training set.
  - Rotating
  - flipping
  - zooming
  - rescaling
- Scaled pixel values to a range between 0 and 1
- Batch Size: set to 40 for the training
- Image Size: set to (224,224) pixels with 3 channels

PYTHON LIBRARIES

STANDARD LIBRARIES LIKE OS, TIME, SHUTIL, PATHLIB

DATA HANDLING LIBRARIES: CV2, NUMPY, PANDAS, SEABORN, MATPLOTLIB.PYPLOT

DEEP LEARNING LIBRARIES: TENSORFLOW AND ITS SUBMODULES.

MODEL

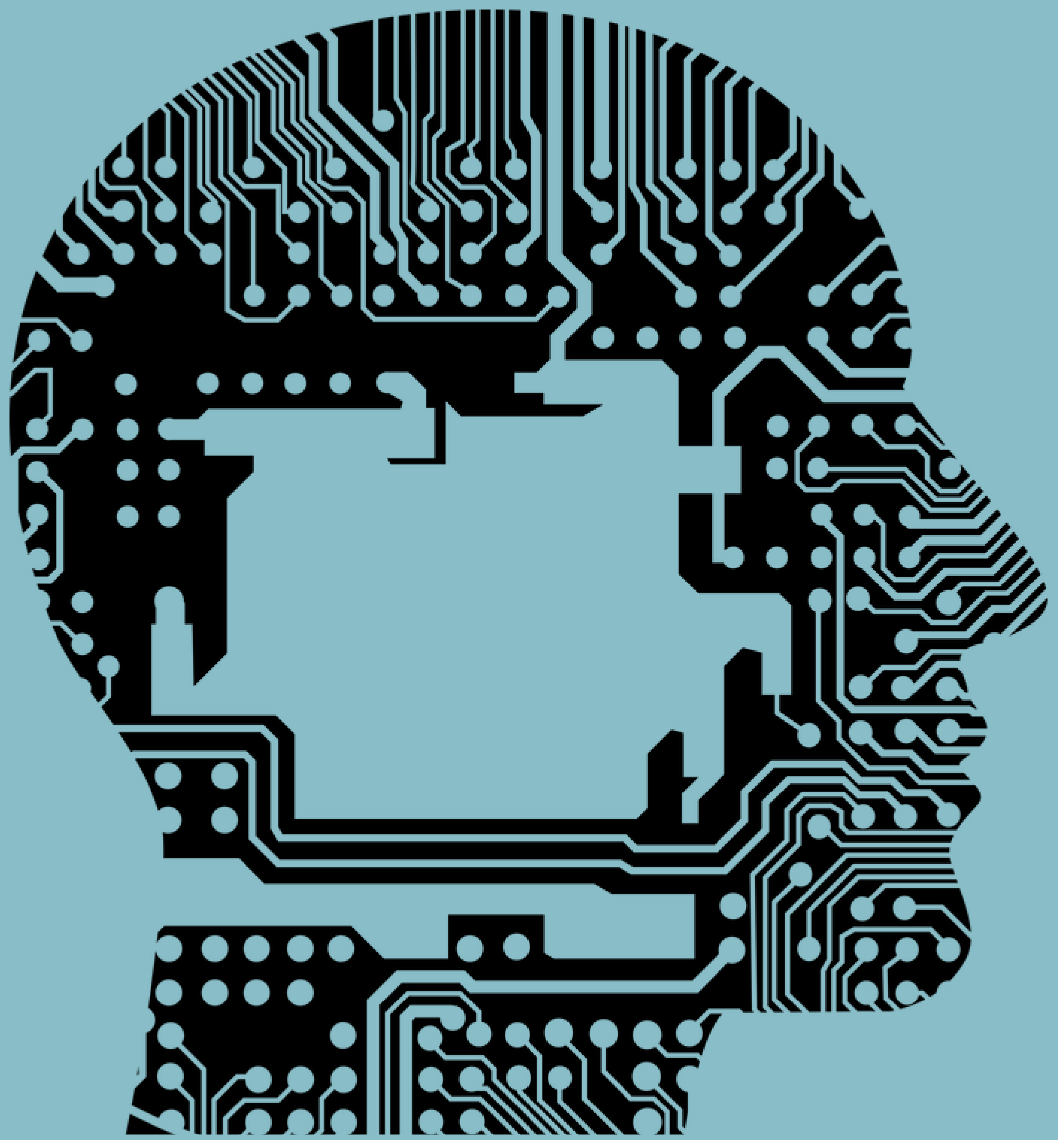
Architecture: Convolutional Neural Network

Layers: Convolutional, MaxPooling, Flatten

Additional layers: Dense layers with dropout for regularization

Activation functions: ReLU for hidden layers, Softmax for output layer

Models

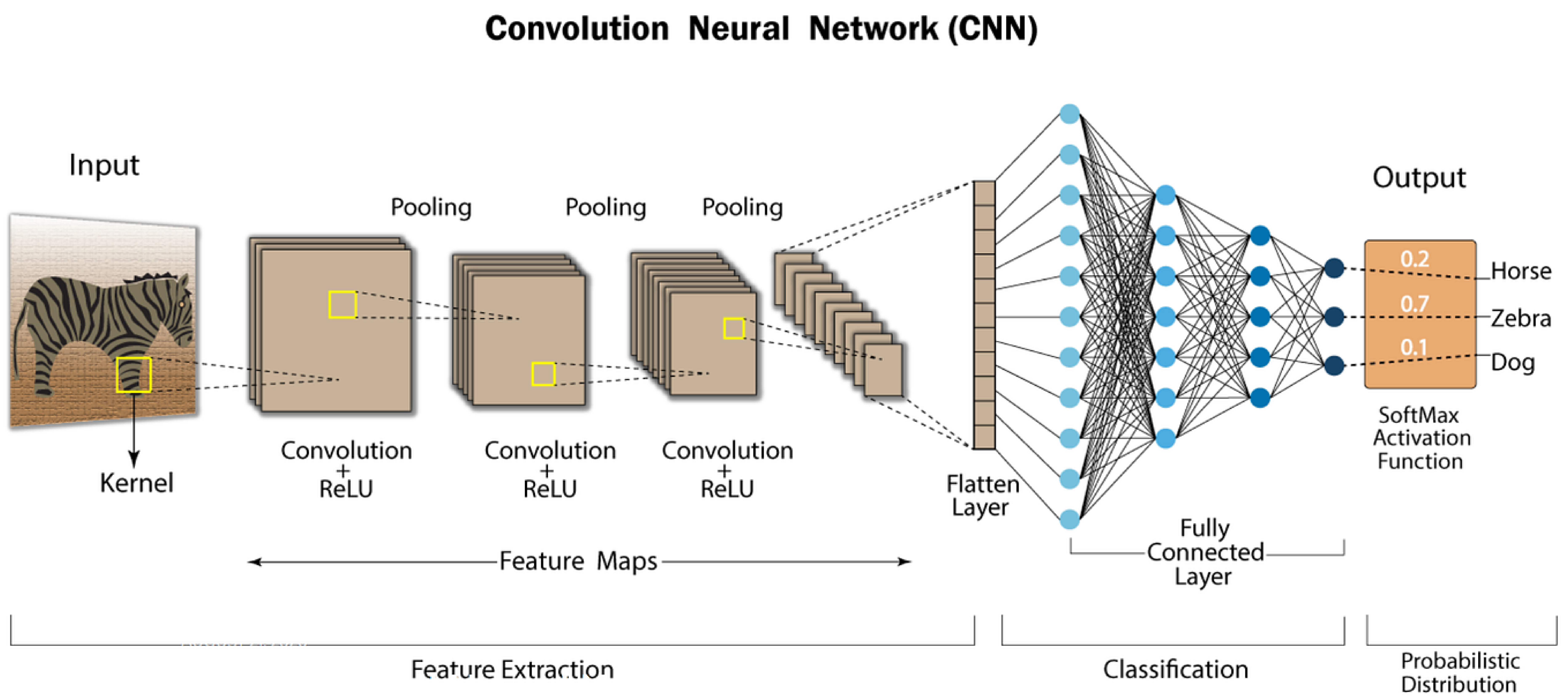


Xception Model

- Pre-trained model: Xception
- Additional layers: Dense layers with dropout for regularization
- Activation functions: ReLU for hidden layers, Softmax for output layer

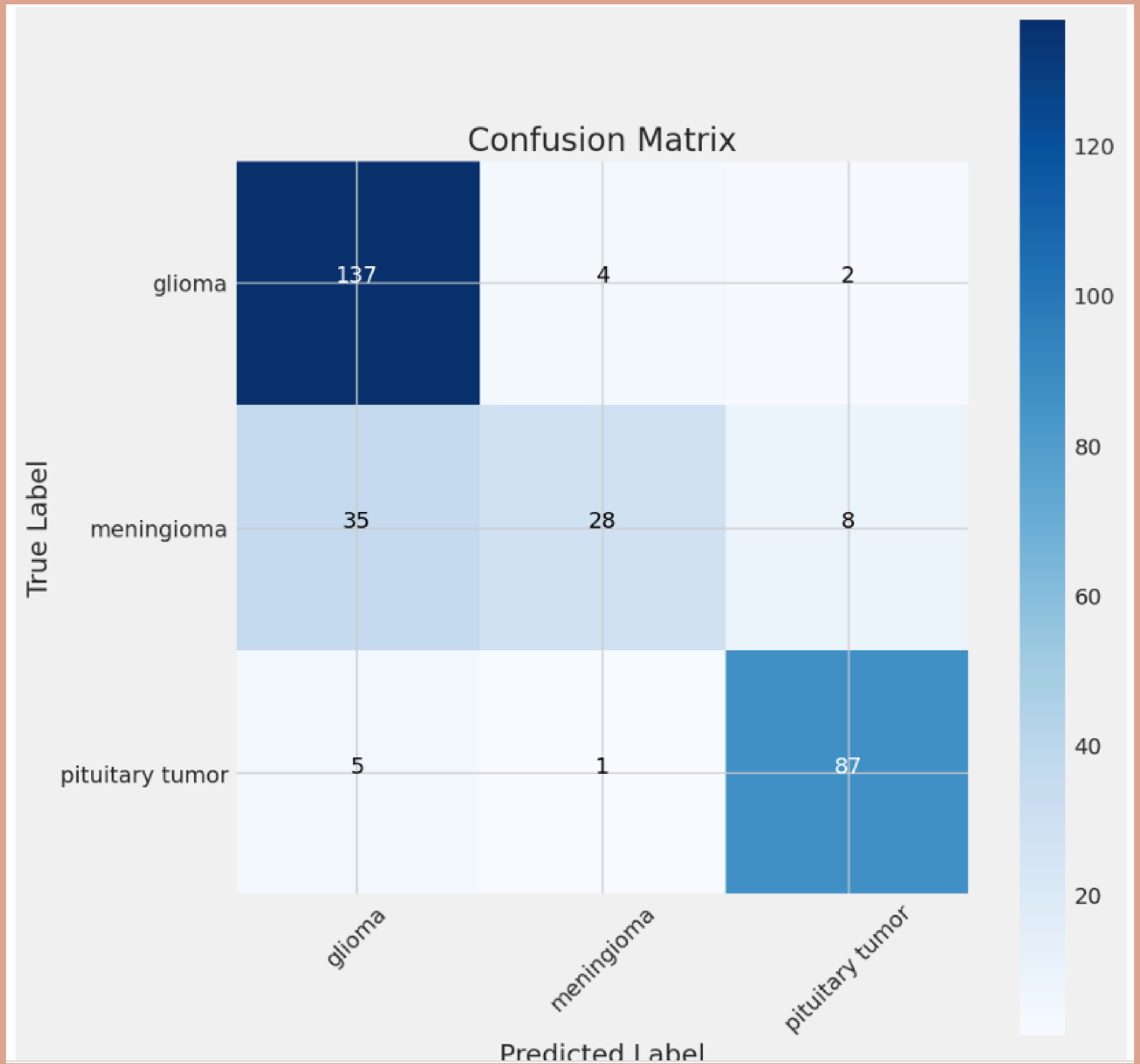
ResNet50

- Pre-trained model: ResNet50
- Additional layers: Dense layers with dropout for regularization
- Activation functions: ReLU for hidden layers, Softmax for output layer


Convolution Neural Network (CNN)
Input
Pooling
Pooling
Pooling
Output
0.2
Horse
0.7
Zebra
0.1
Dog
Kernel
Convolution + ReLU
Convolution + ReLU
Convolution + ReLU
Flatten Layer
SoftMax Activation Function
Fully Connected Layer
Feature Maps
Feature Extraction
Classification
Probabilistic Distribution

Confusion Matrics and Classification Report

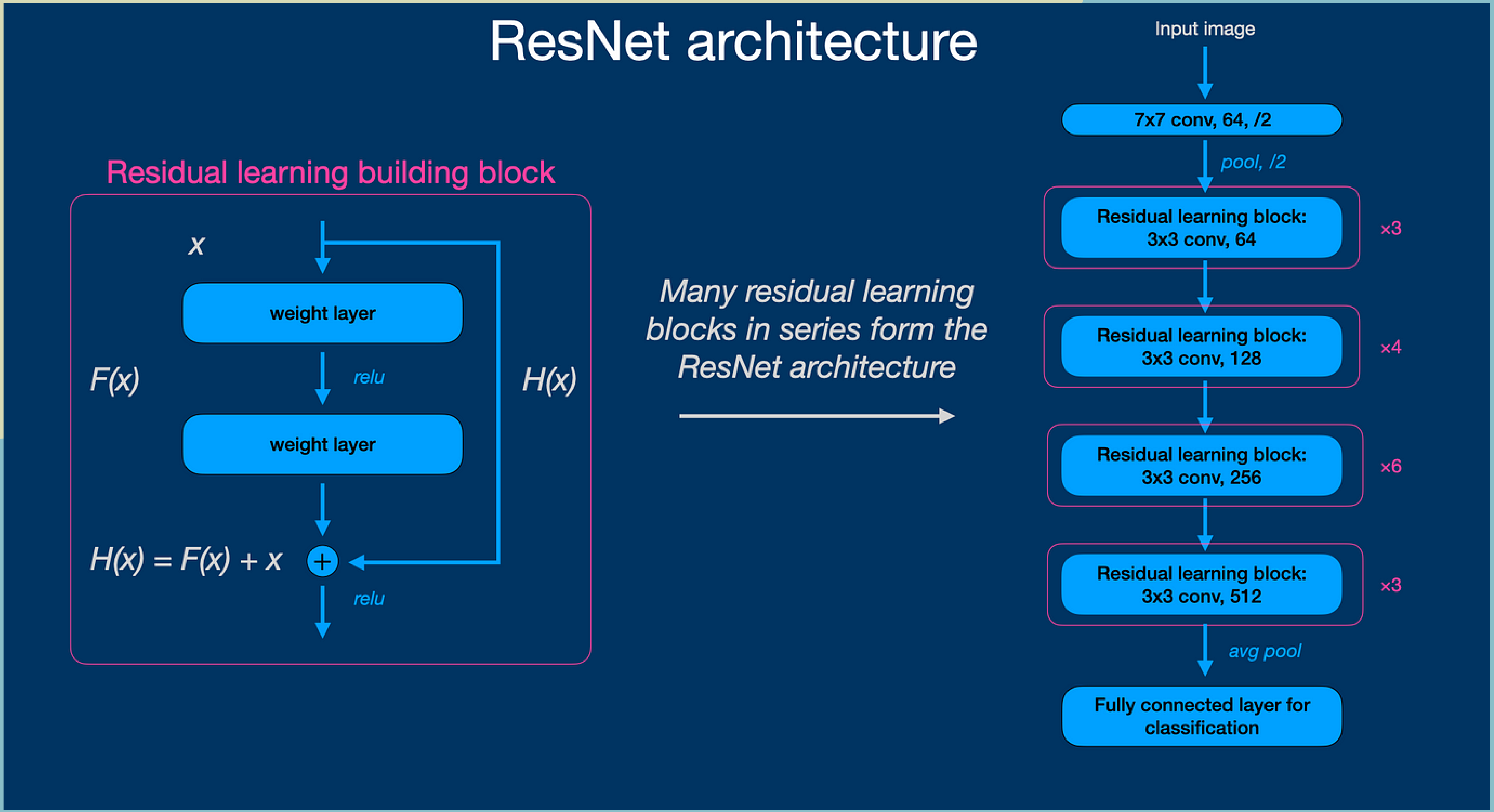
Generic CNN



GENERIC CNN

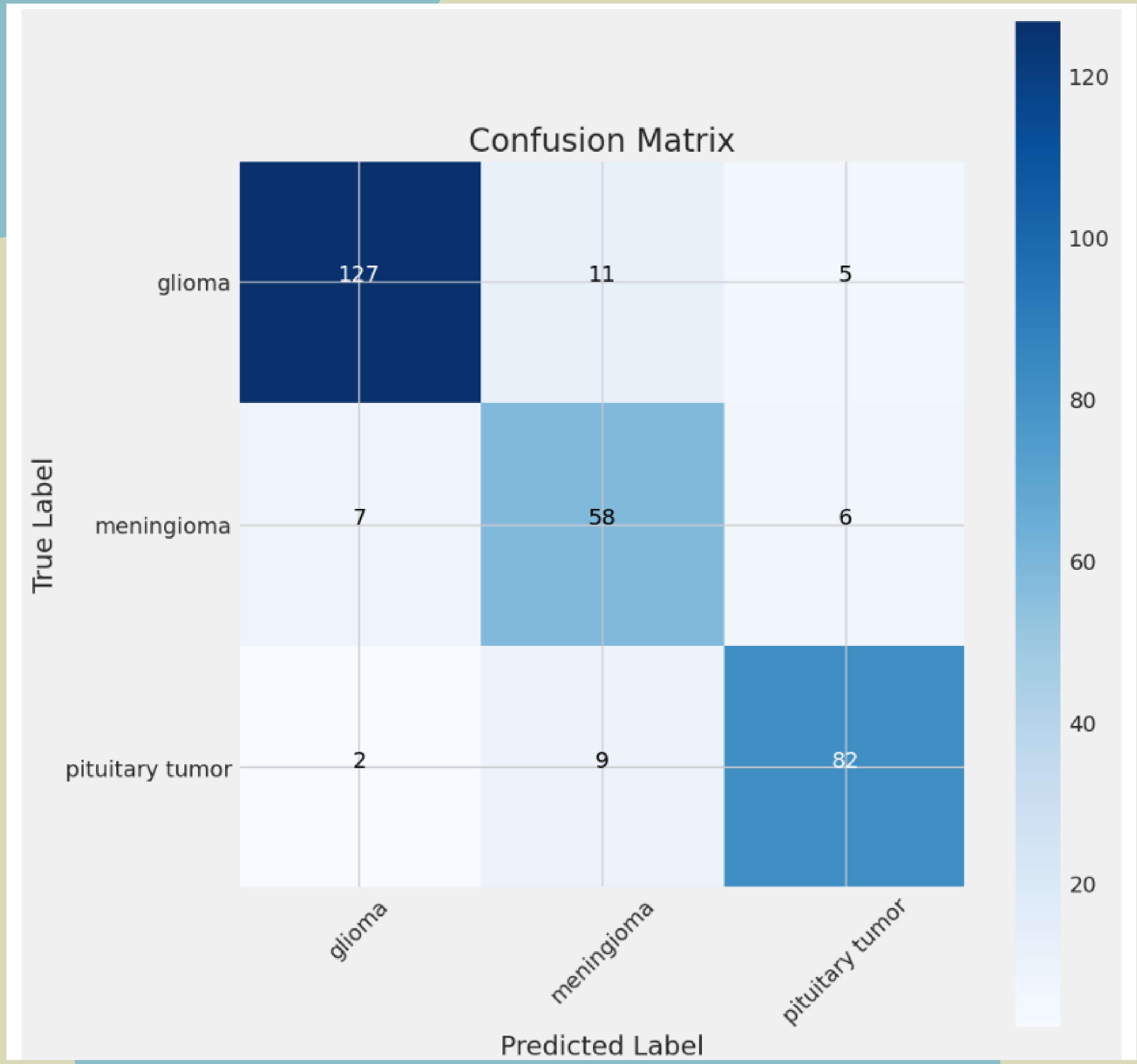
```
plot_training(history)
```

RESNET ARCHITECTURE



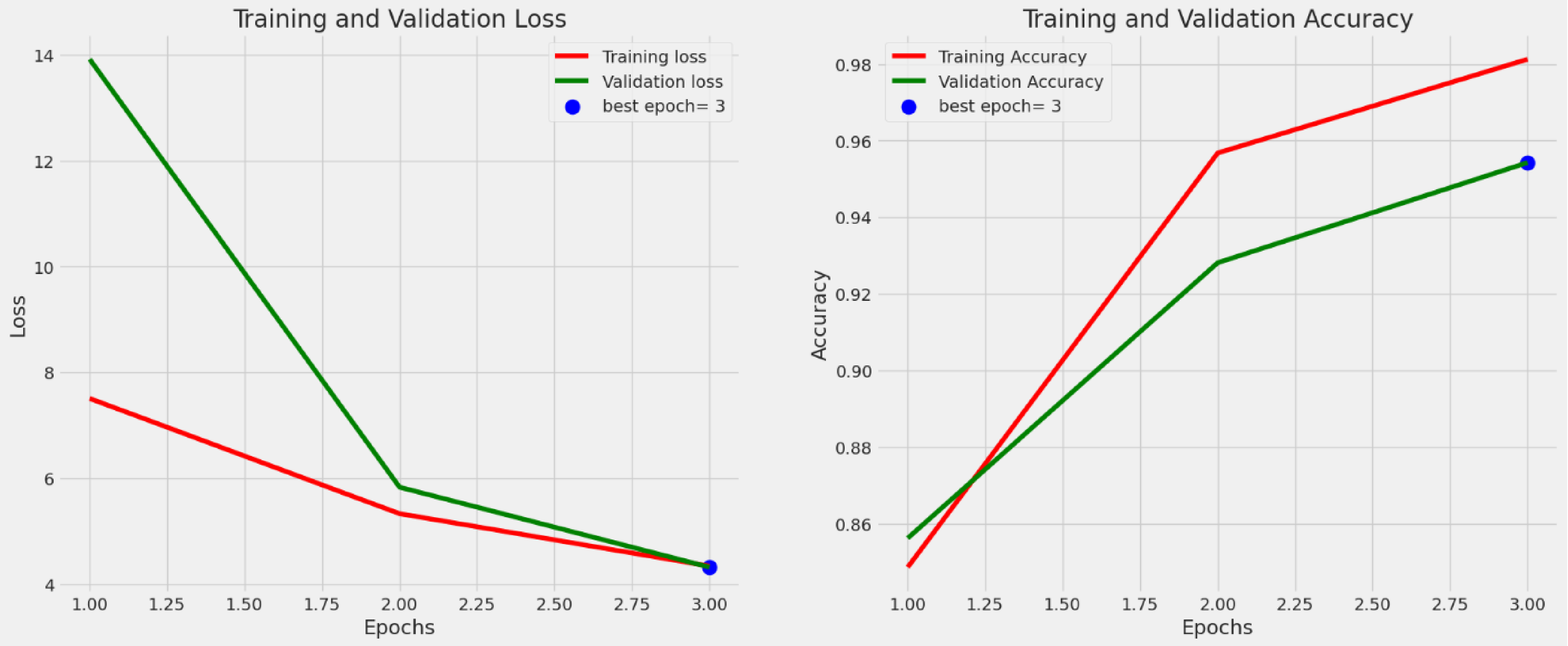
CONFUSION MATRICS AND CLASSIFICATION REPORT

RESNET50



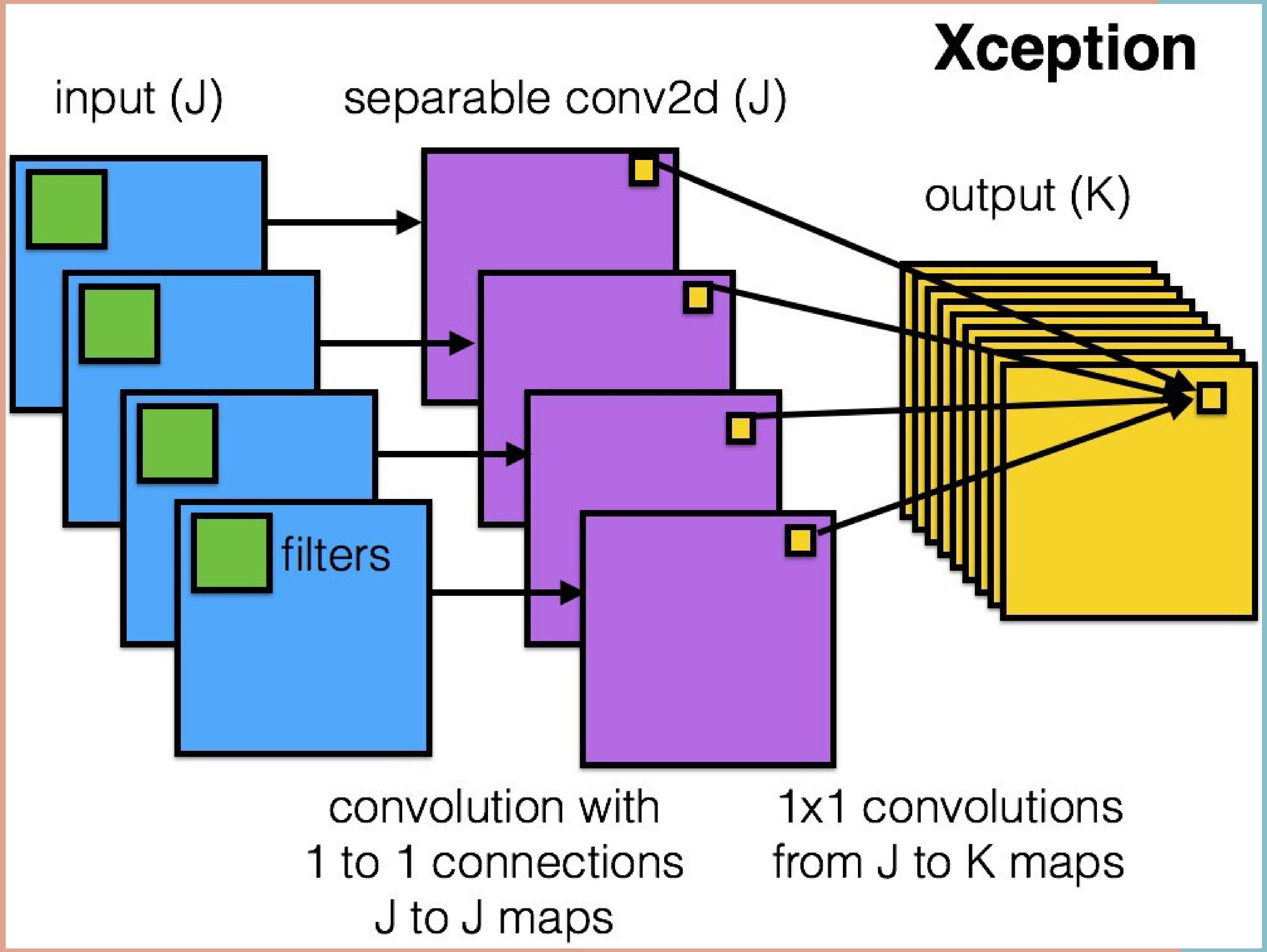
RESNET50

```
plot_training(history)
```



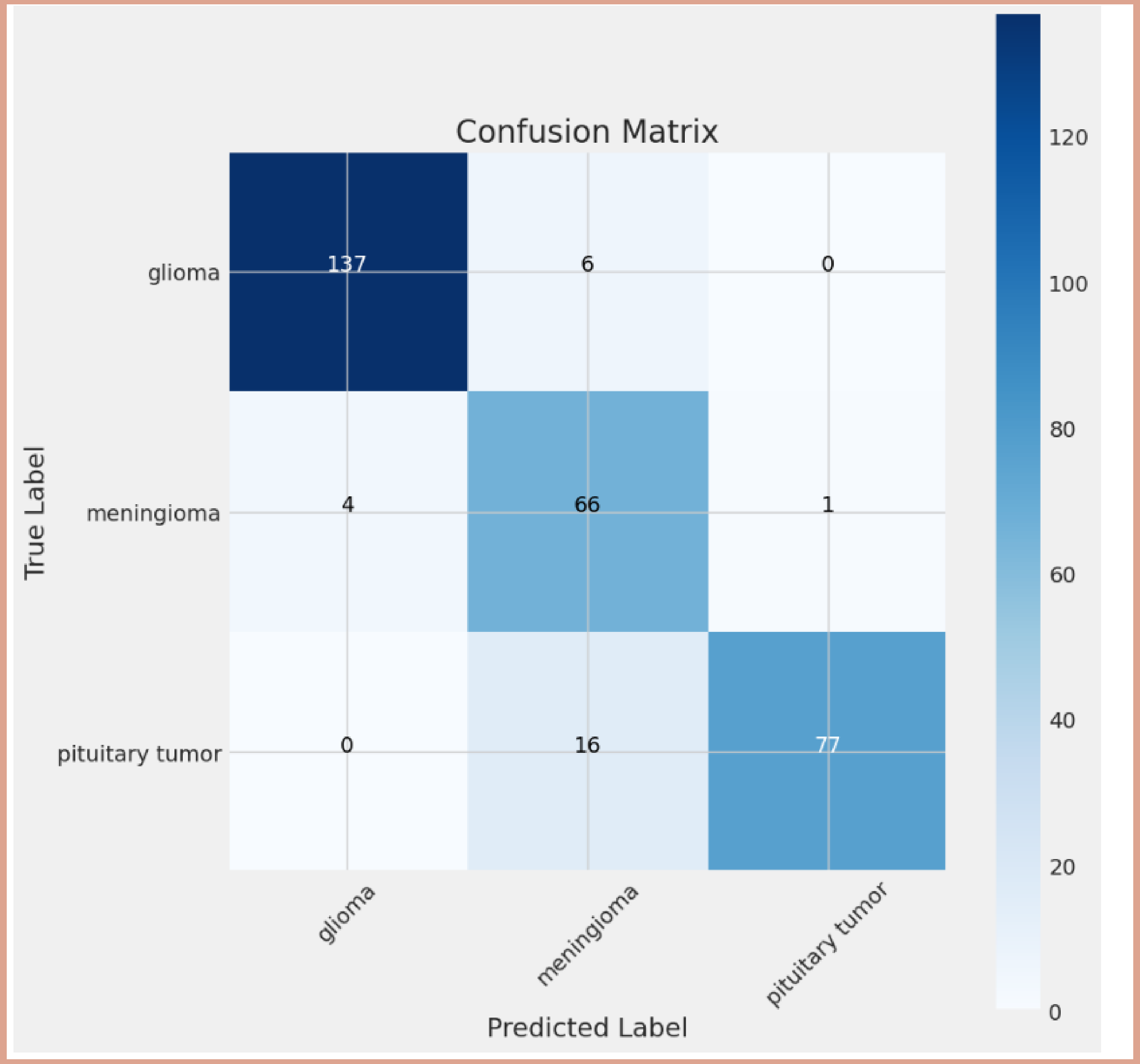
+ Code + Markdown

XCEPTION MODEL



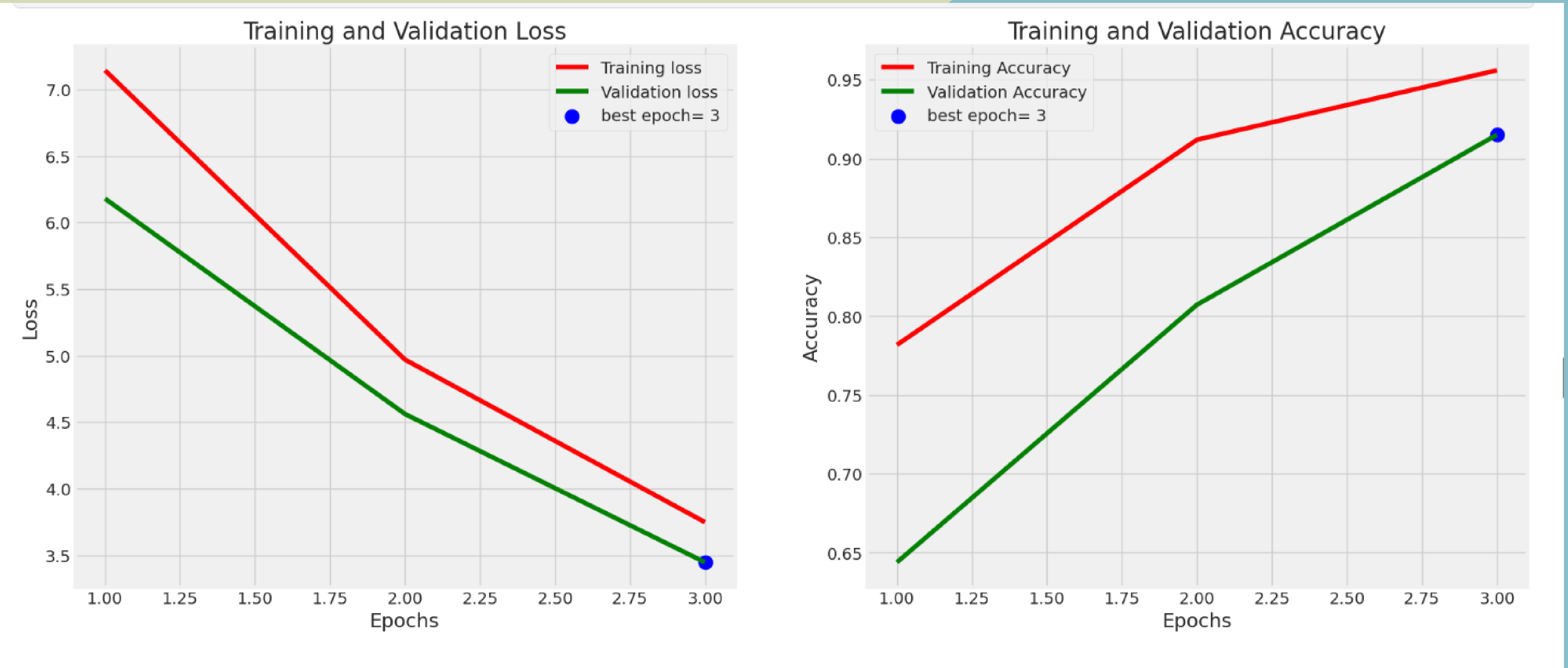
CONFUSION MATRICS AND CLASSIFICATION REPORT

XCEPTION



TRAINING AND VALIDATION: BEST EPOCH

XCEPTIONAL



MODEL EVALUATION

Generic CNN

Evaluation Metrics:

- Train Loss: 3.72
- Train Accuracy: 86%
- Validation Loss: 3.85
- Validation Accuracy: 80%
- Test Loss: 3.83
- Test Accuracy: 82%

Xceptional

Evaluation Metrics:

- Train Loss: 3.4
- Train Accuracy: 96%
- Validation Loss: 3.44
- Validation Accuracy: 91.5%
- Test Loss: 3.44
- Test Accuracy: 91.2

ResNet50

Evaluation Metrics:

- Train Loss: 12.36
- Train Accuracy: 89%
- Validation Loss: 13.91
- Validation Accuracy: 85.6%
- Test Loss: 12.36
- Test Accuracy: 86.9%

CONCLUSION

The ability to swiftly and accurately detect the presence of brain tumors holds profound implications for expediting the diagnostic process and subsequently initiating timely treatment for patients.

The model's high accuracy indicates its efficacy in discriminating between tumor and non-tumor cases, thereby offering a reliable and efficient tool for healthcare practitioners

The expedited detection facilitated by this machine learning model not only reduces the time taken for diagnosis but also opens avenues for prompt intervention and treatment planning.

LESSONS LEARNT

In the comparison between ResNet50, Xception, and a generic Convolutional Neural Network (CNN), the Xception model emerged as the superior choice for the given task

Xception, with its depthwise separable convolutions and hierarchical feature learning, demonstrated a more sophisticated ability to capture complex patterns and hierarchical representations in the dataset.

ResNet50, while effective, may face challenges with vanishing gradients and optimization difficulties in very deep networks, potentially limiting its performance on certain tasks.

The Generic CNN, lacking the specialized architectural innovations of Xception, may struggle to learn intricate features compared to the more advanced models.