

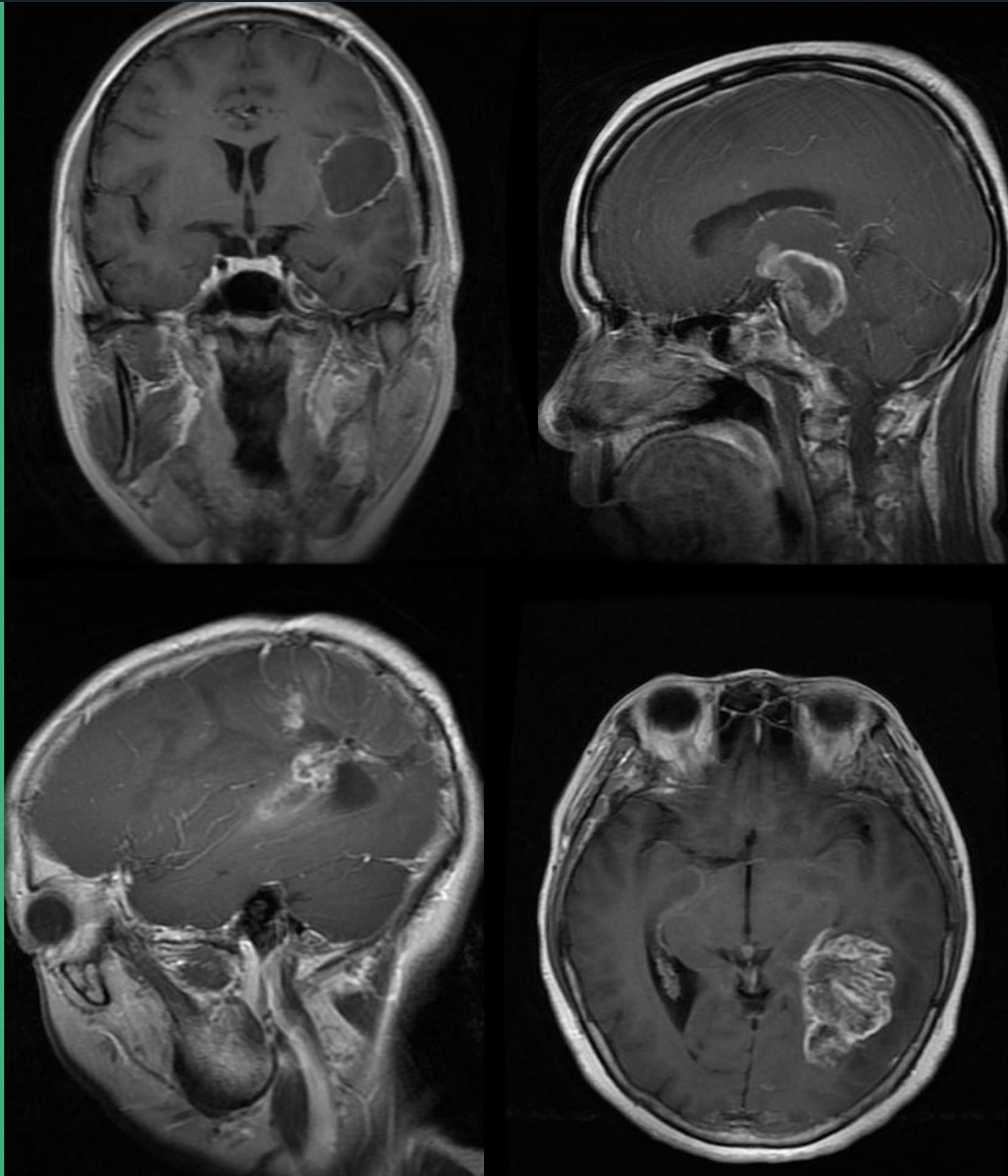
# Comparative study of neural learning methods in the context of brain tumor classification

Classification of Brain Tumors using brain MRIs

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# Motivation

- Each year, approximately 70,000-170,000 cancer patients are diagnosed with brain tumors, while ~100,000 will die every year as a result of brain metastases
- Malignant brain tumors cause an average of 20 Years of Potential Life Lost
- Detection and classification of such cancers help us understand the science, evolution, and how best to treat them.



# Agenda

## Objective

## EDA

## and

## Preprocessing

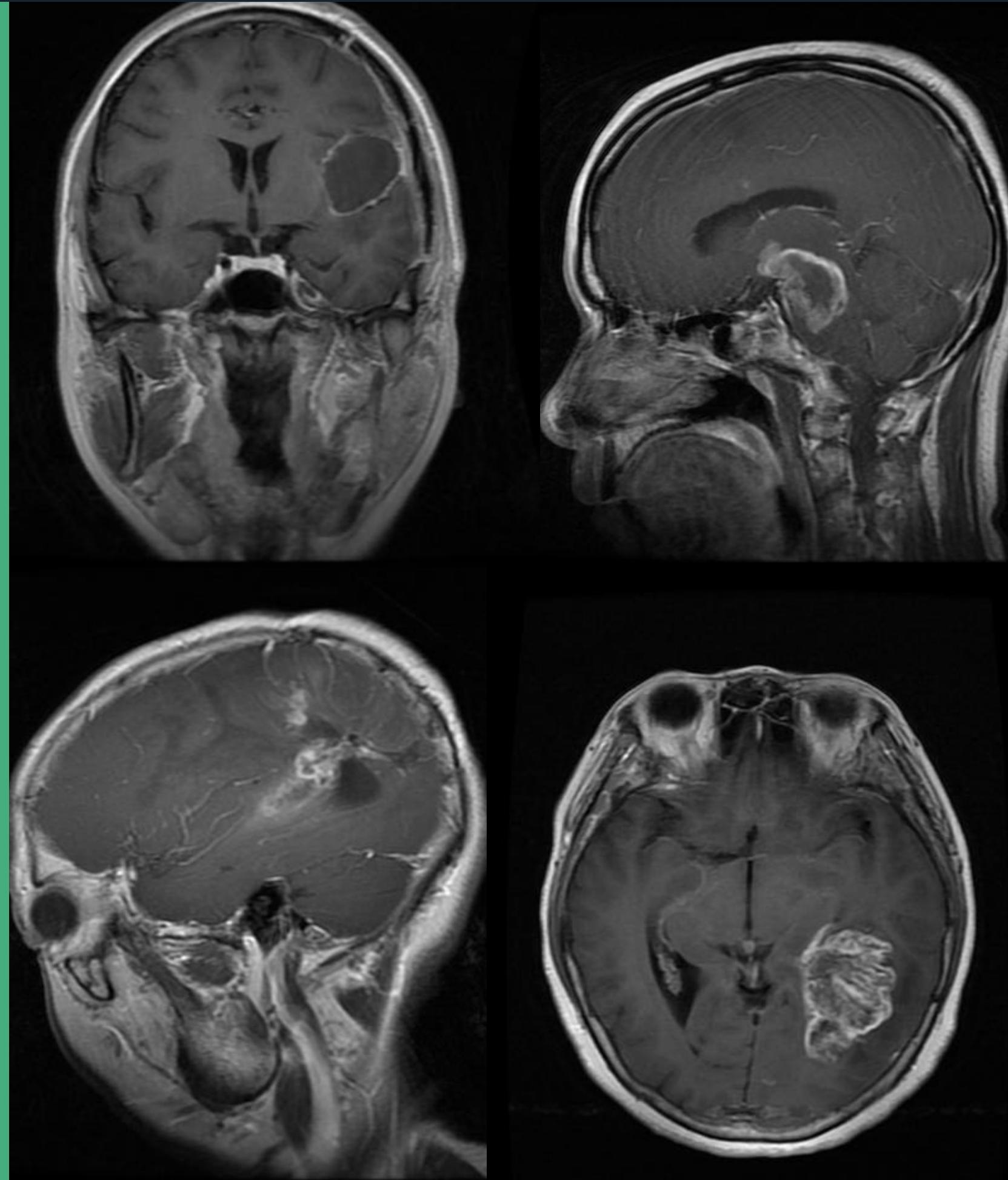
## Models

## Evaluation Metrics

- To classify MR images of the brain into types of tumors
  - Compare the results of the models to choose the best model for MR image classification.
- 
- Identifying class imbalance
  - Grid Plots
  - Image Ratios
  - Image cropping and re-sizing
  - Image augmentation
  - Interpolation
- 
- CNN, VGG16, InceptionV3, Resnet50
- 
- Loss, Accuracy

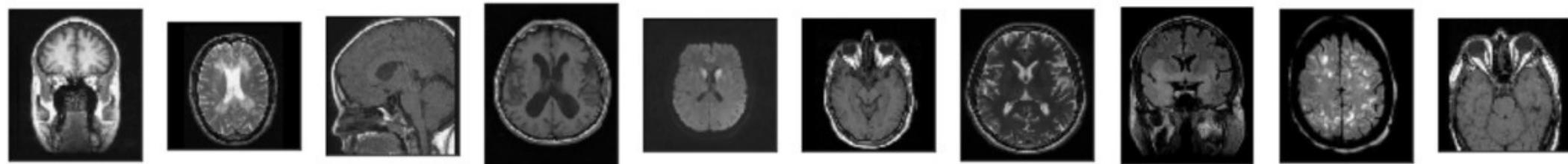
# Data Description

- The dataset is a coalition of two different datasets of 3264 and 435 MRI scans of the brain
- They are divided into 4 classes - Glioma Tumor, Meningioma Tumor, Pituitary Tumor and one class of normal tumor free brains
- These 3699 images are used to train and test on the model

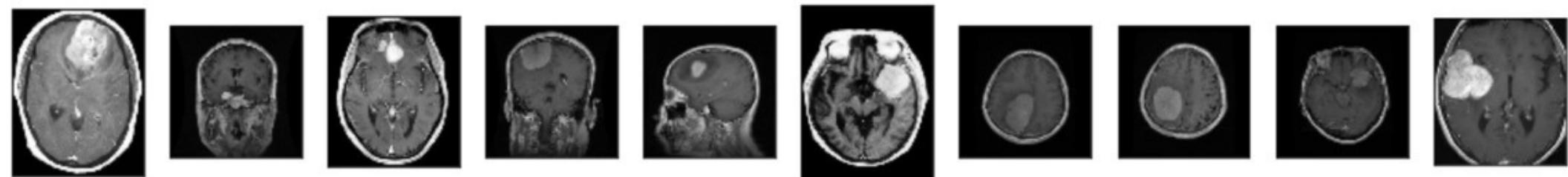


# EDA

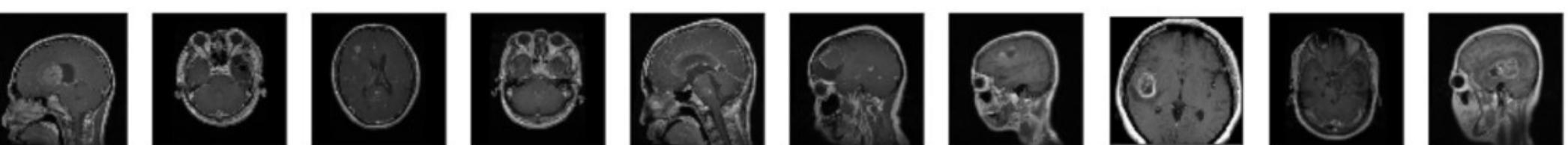
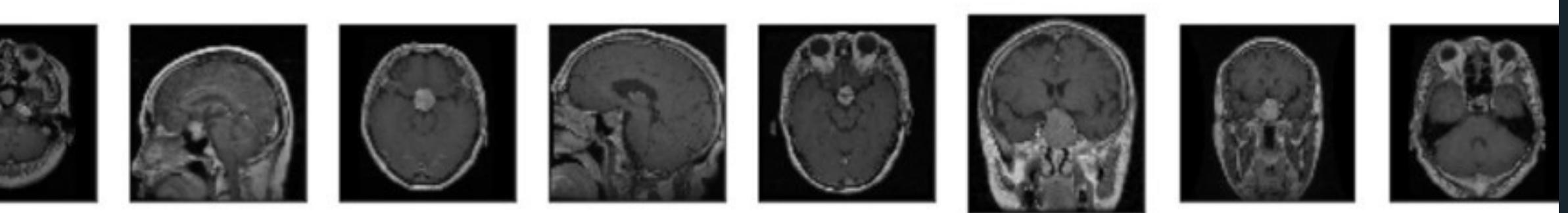
# Grid Plots



Tumor: PITUITARY\_TUMOR



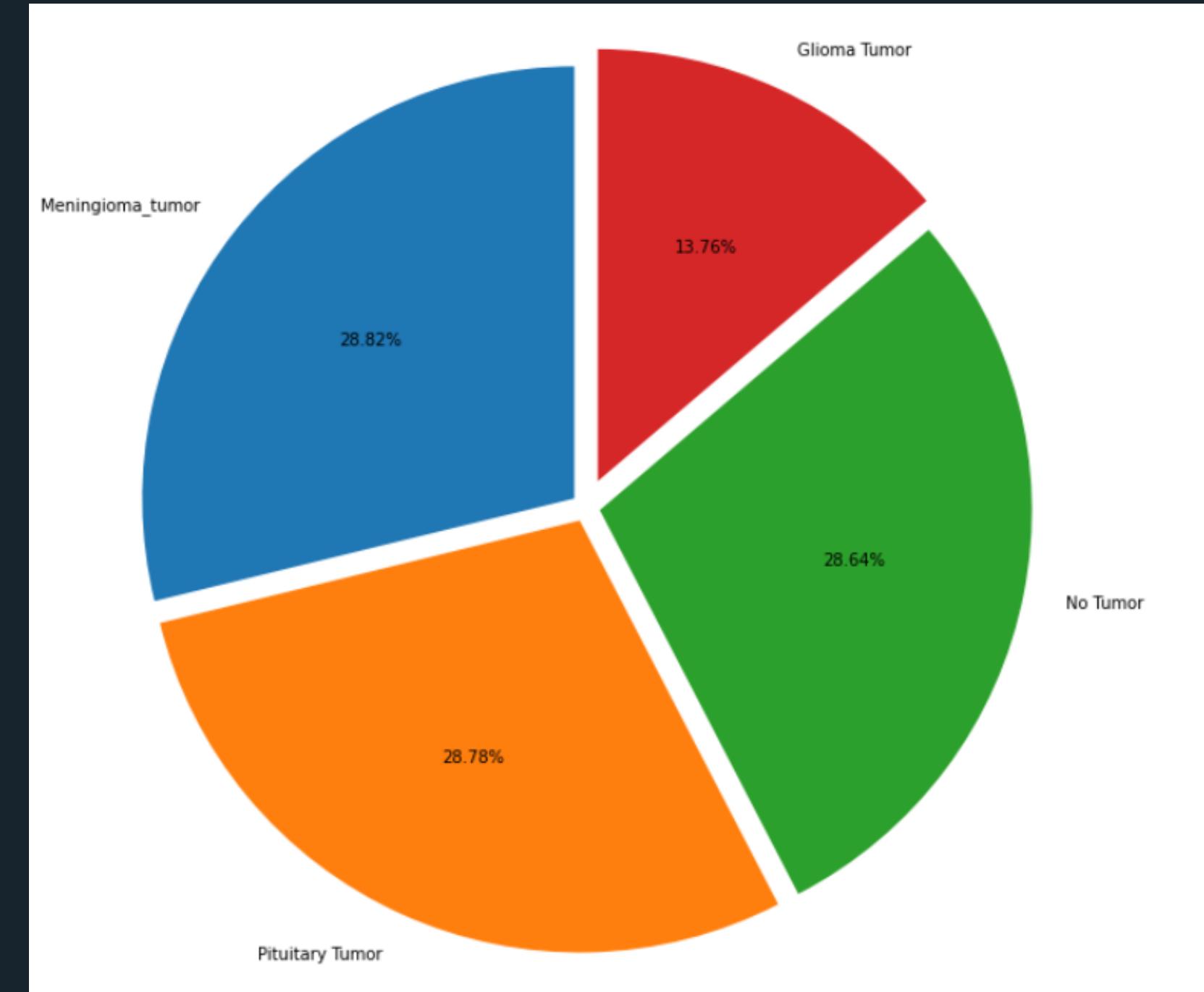
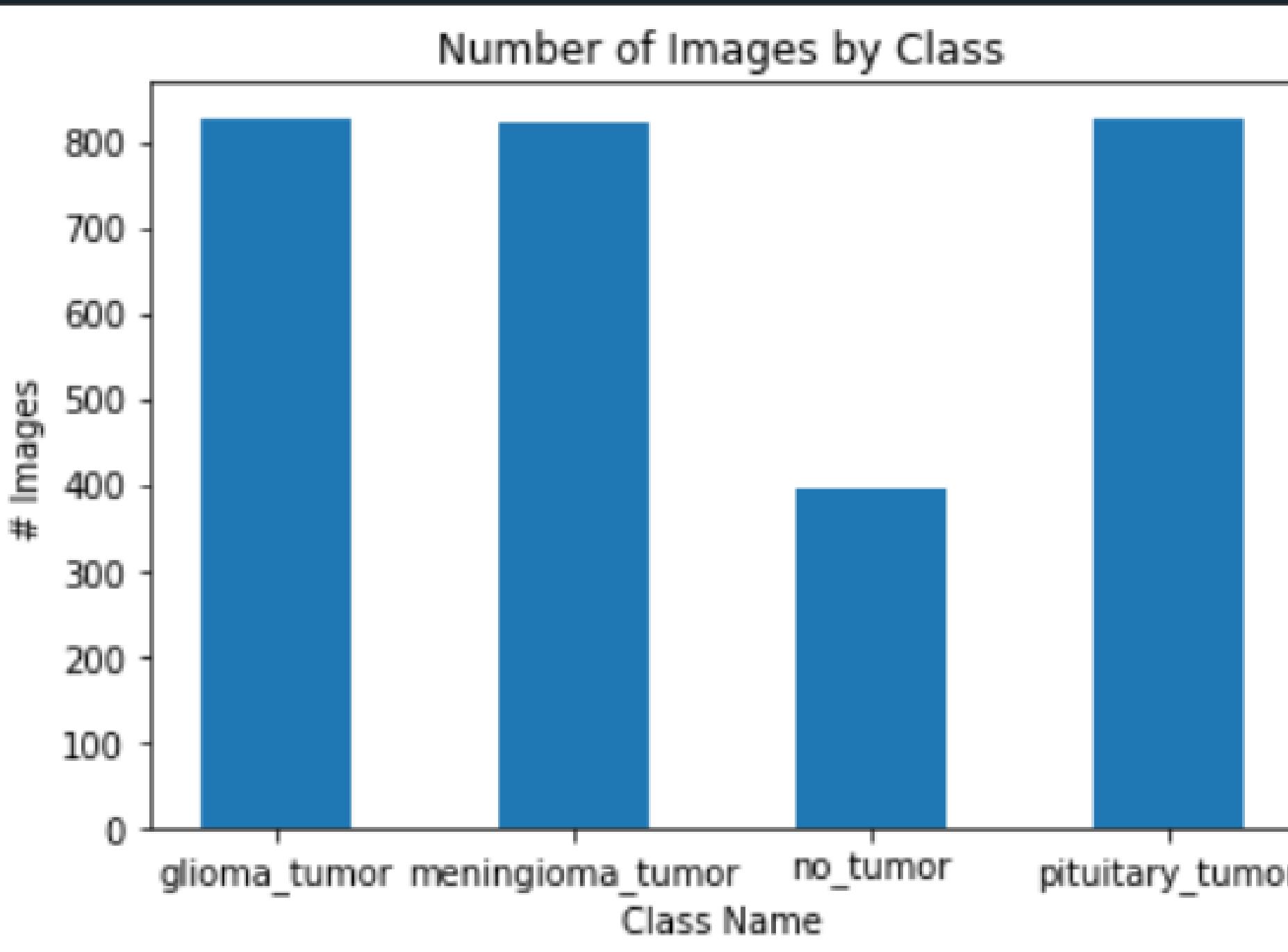
Tumor: NO\_TUMOR



Tumor: MENINGIOMA\_TUMOR

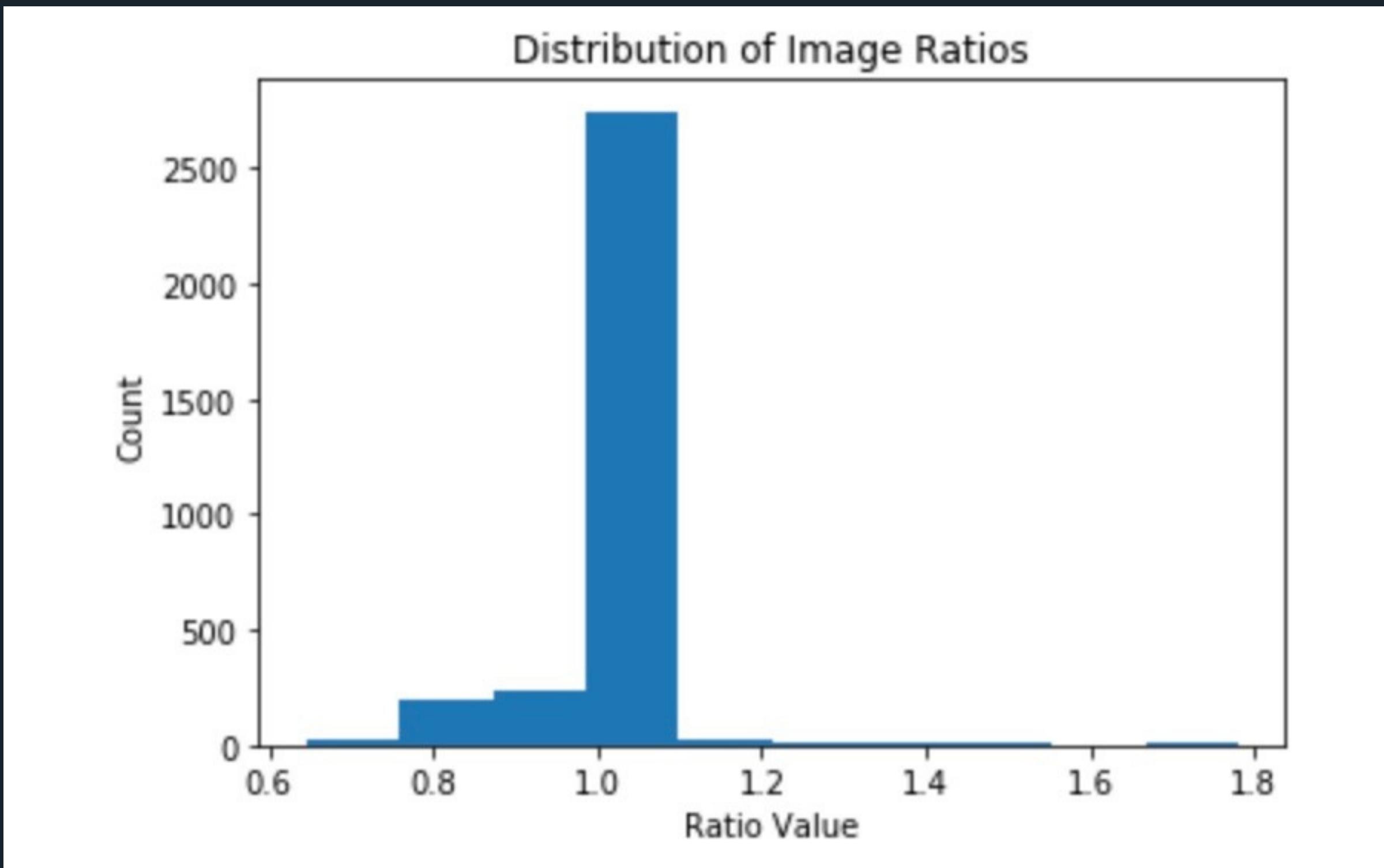
# EDA

## Identifying class imbalance



# EDA

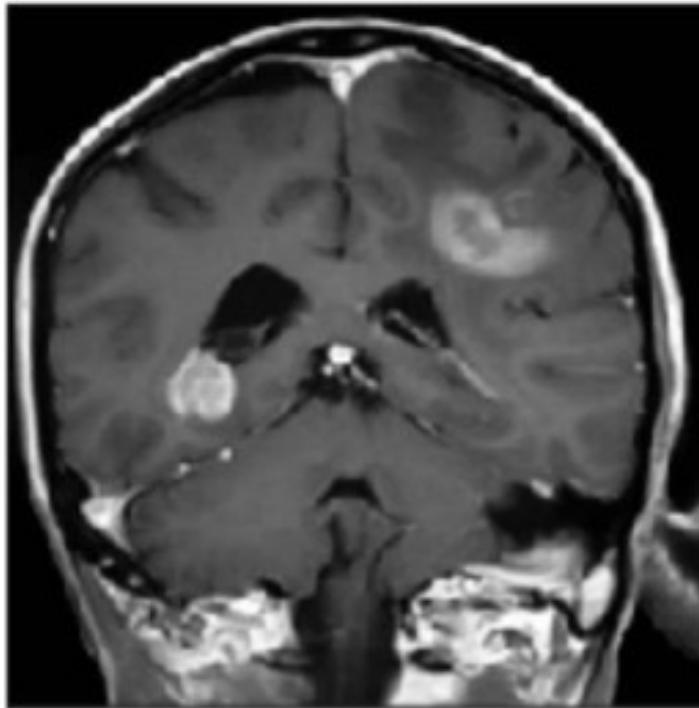
## Image ratio



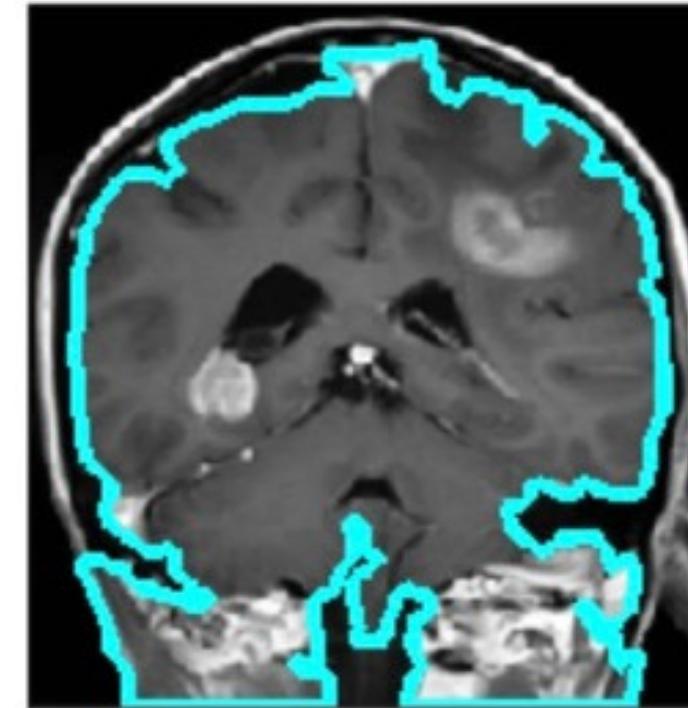
# Preprocessing

## Image cropping and re-sizing

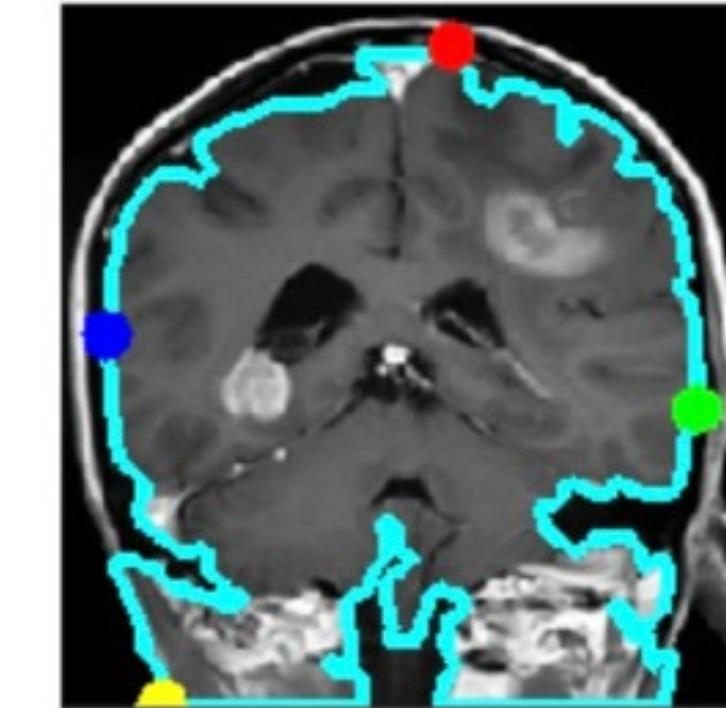
Step 1. Get the original image



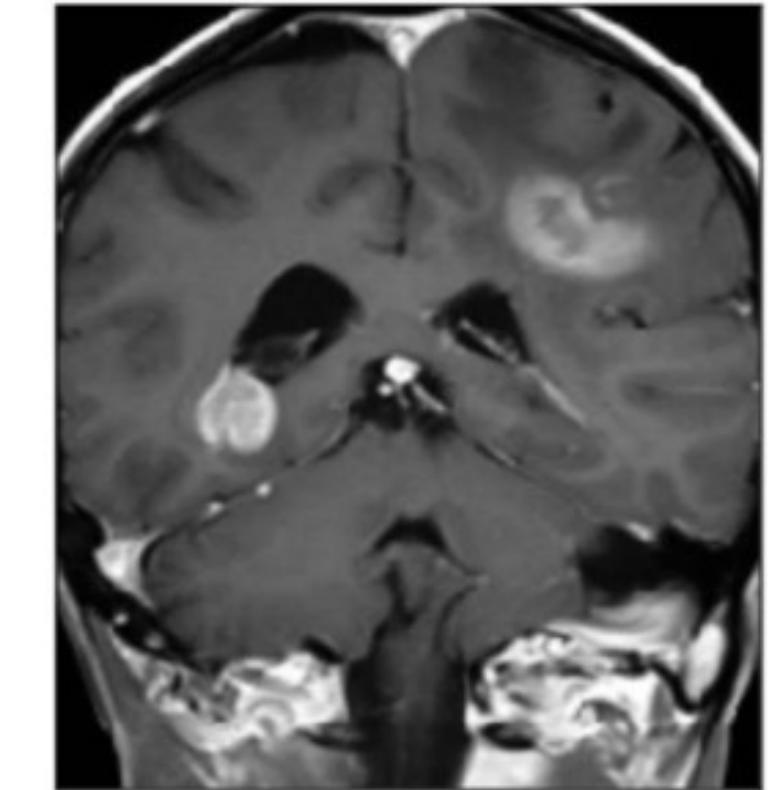
Step 2. Find the biggest contour



Step 3. Find the extreme points

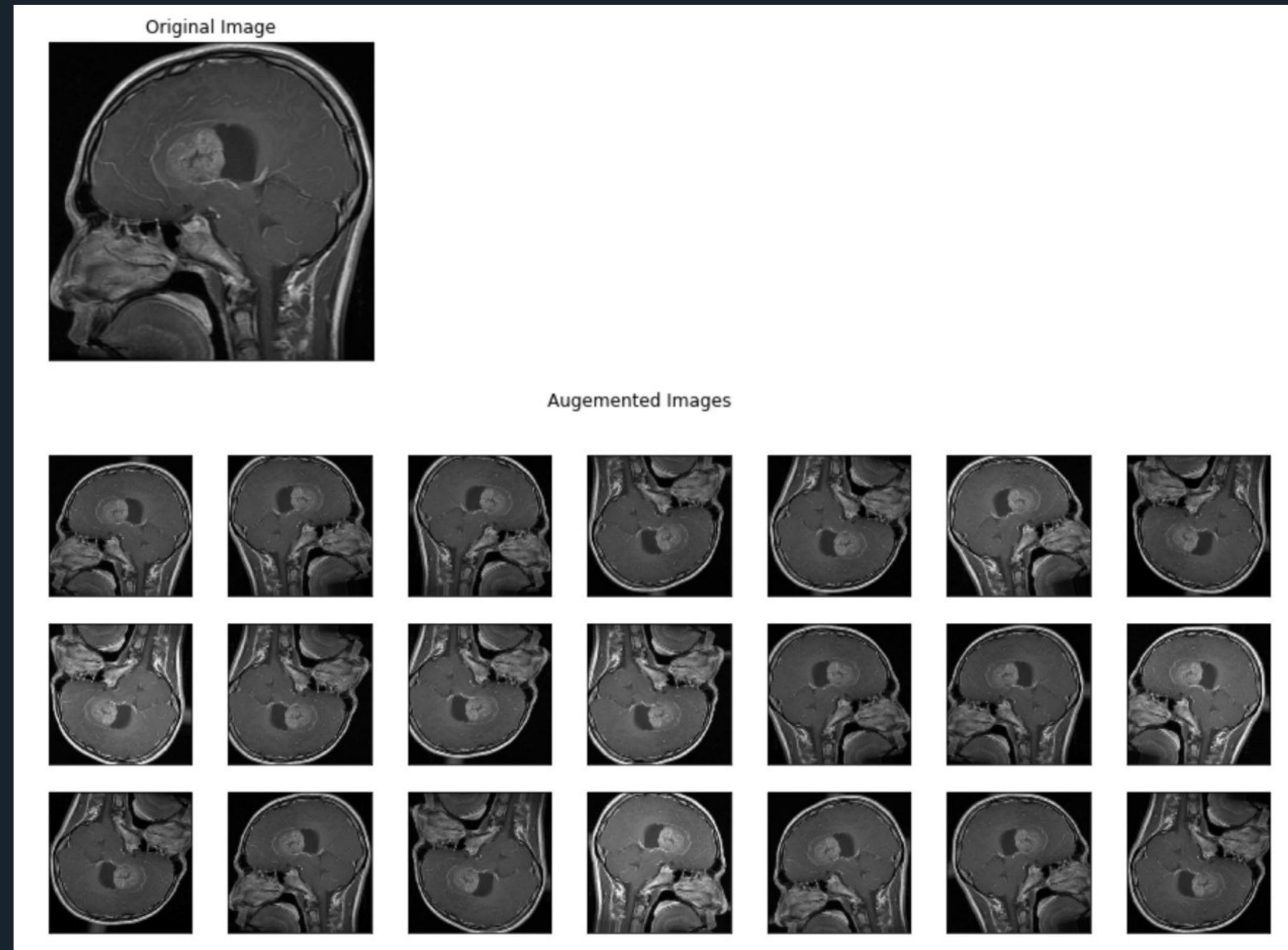


Step 4. Crop the image



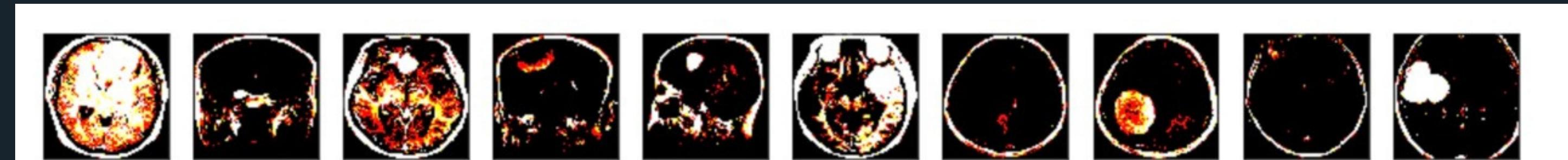
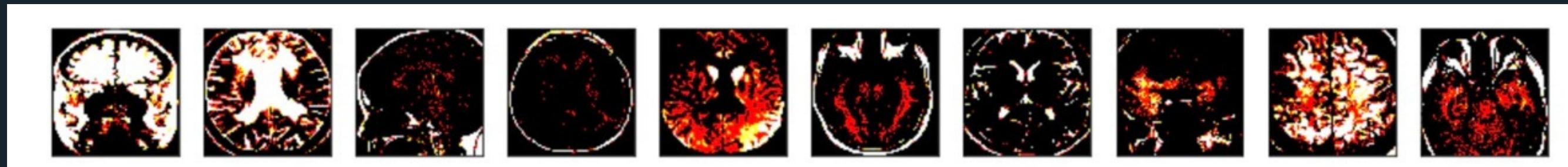
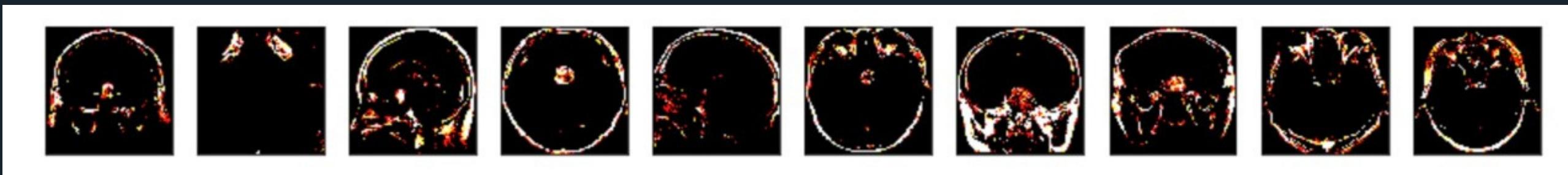
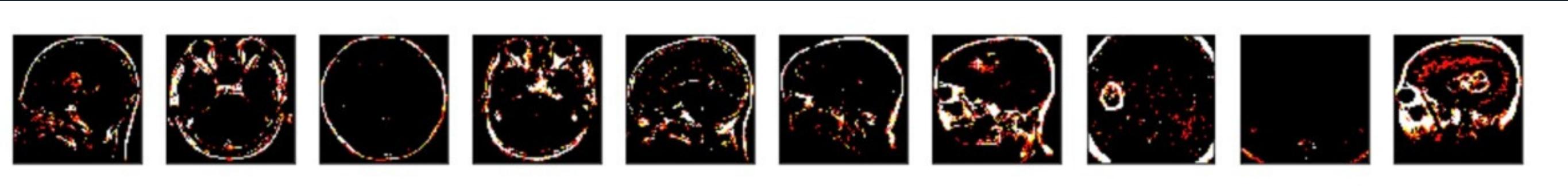
# Preprocessing

## Image Augmentation



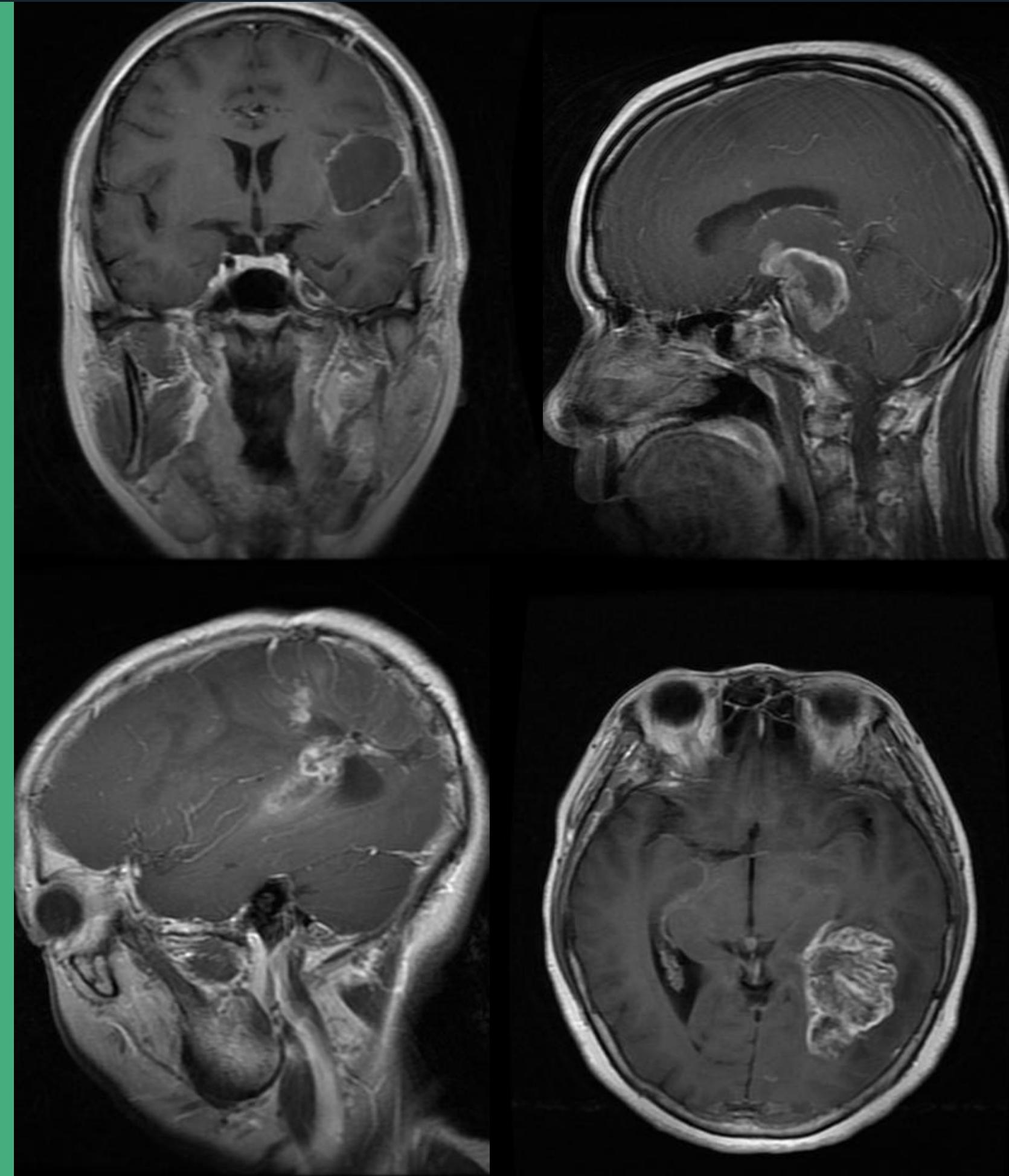
# Preprocessing

## Image Interpolation

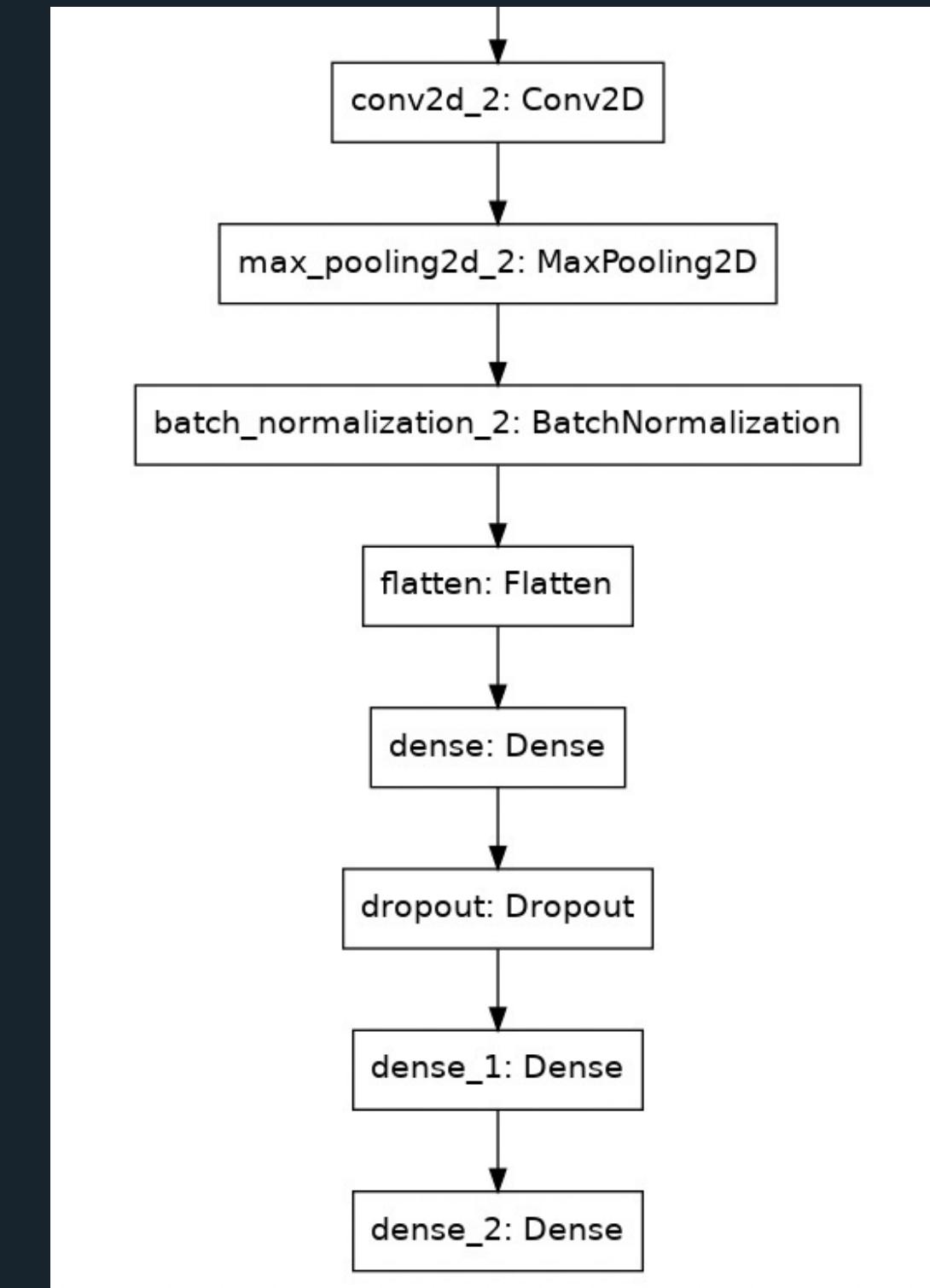
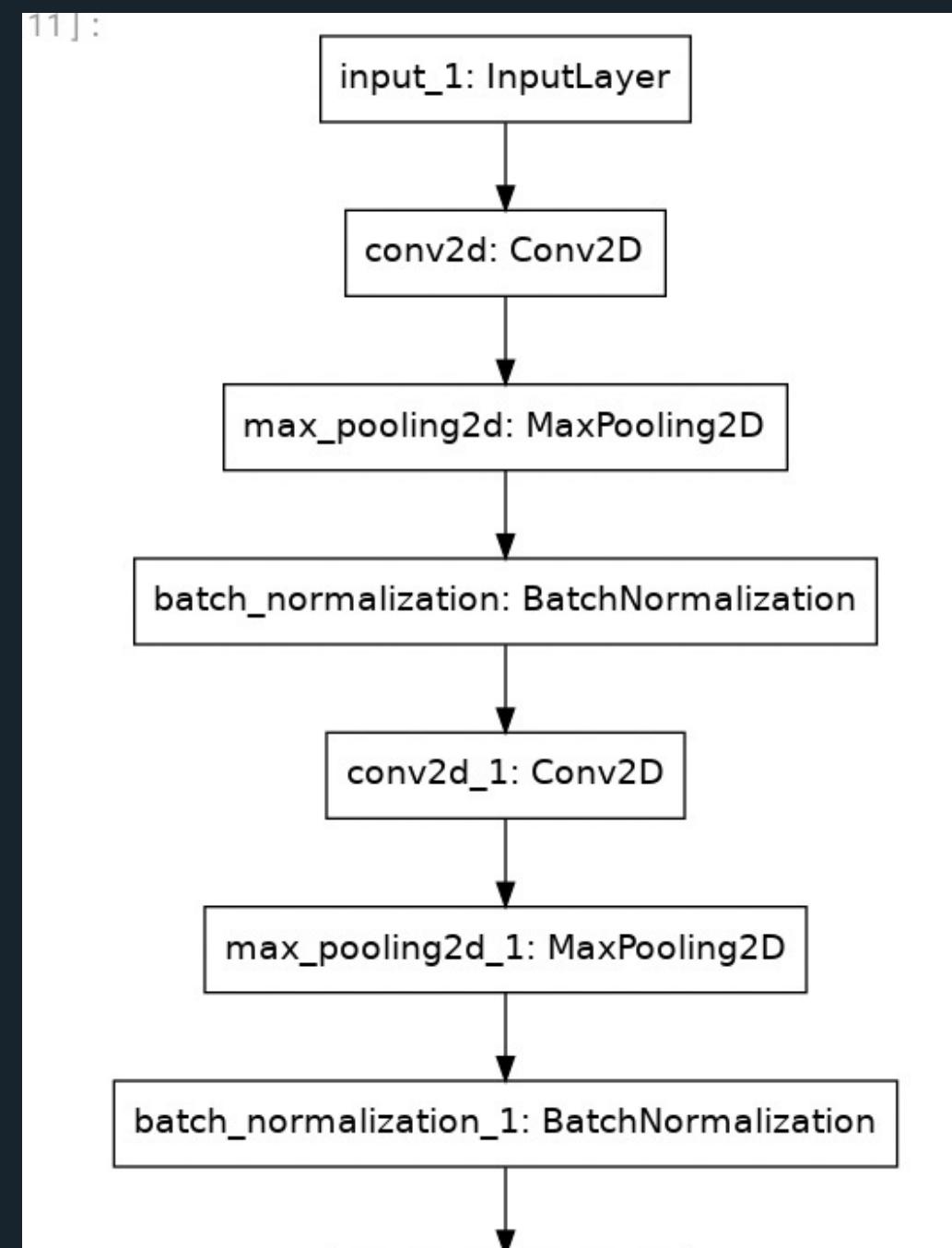


# Models

- We are using a Dense CNN as a baseline for our comparison
- Pre-trained models were chosen to compare against the CNN model
- Transfer Learning models VGG16, ResNet 50 and InceptionV3 are used to see how they perform against the same dataset

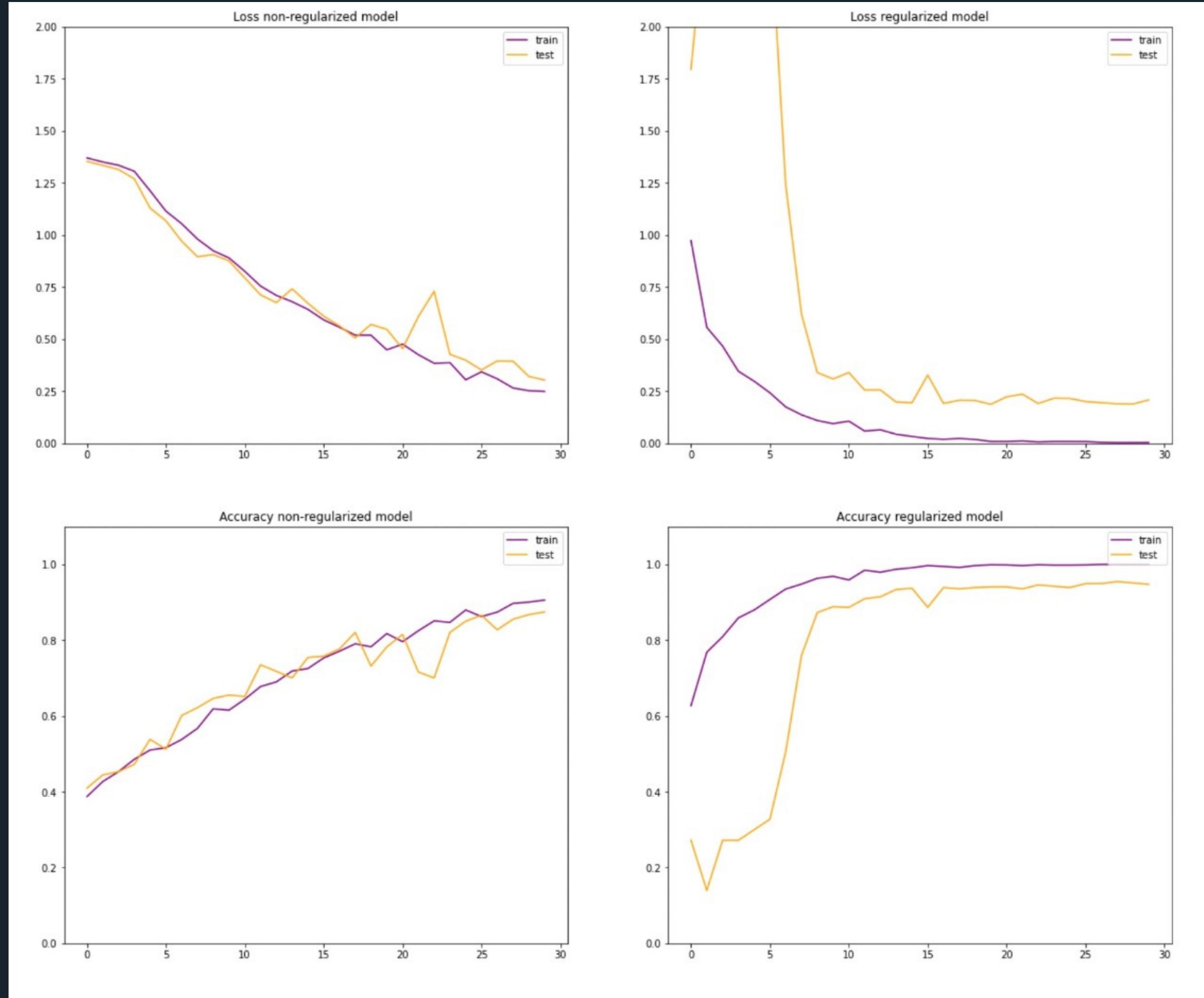


# Convolutional Network



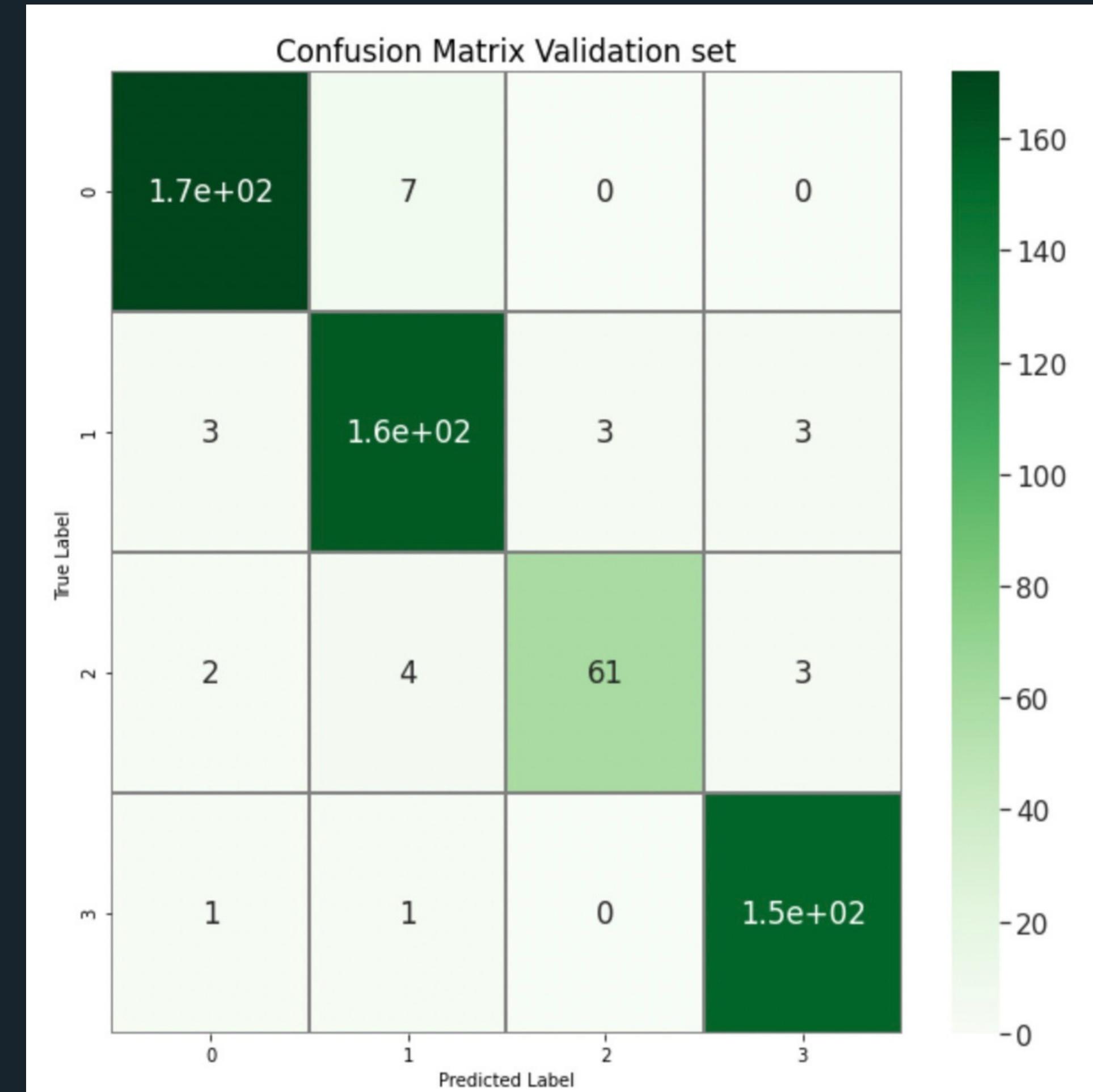
# Loss and Accuracy

CNN



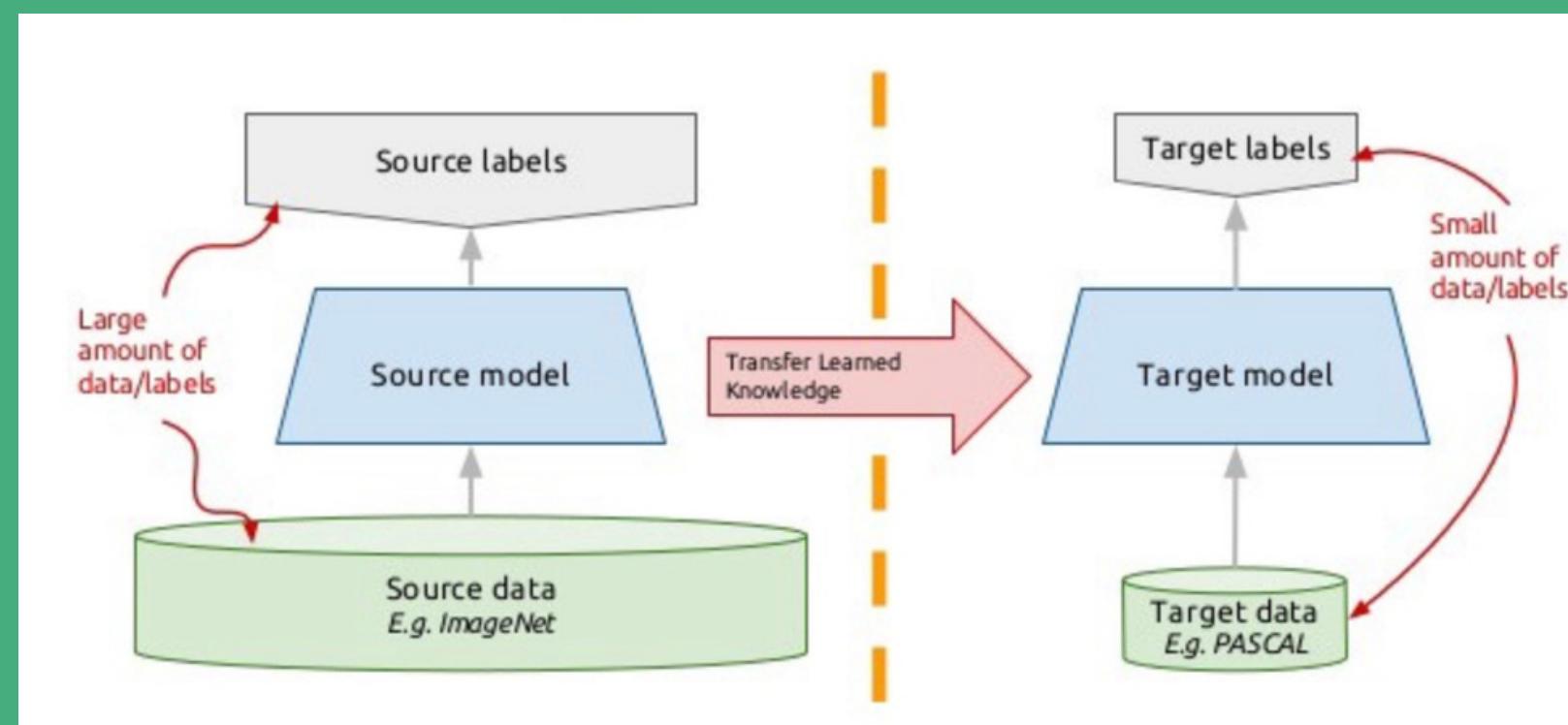
# Confusion Matrix

CNN

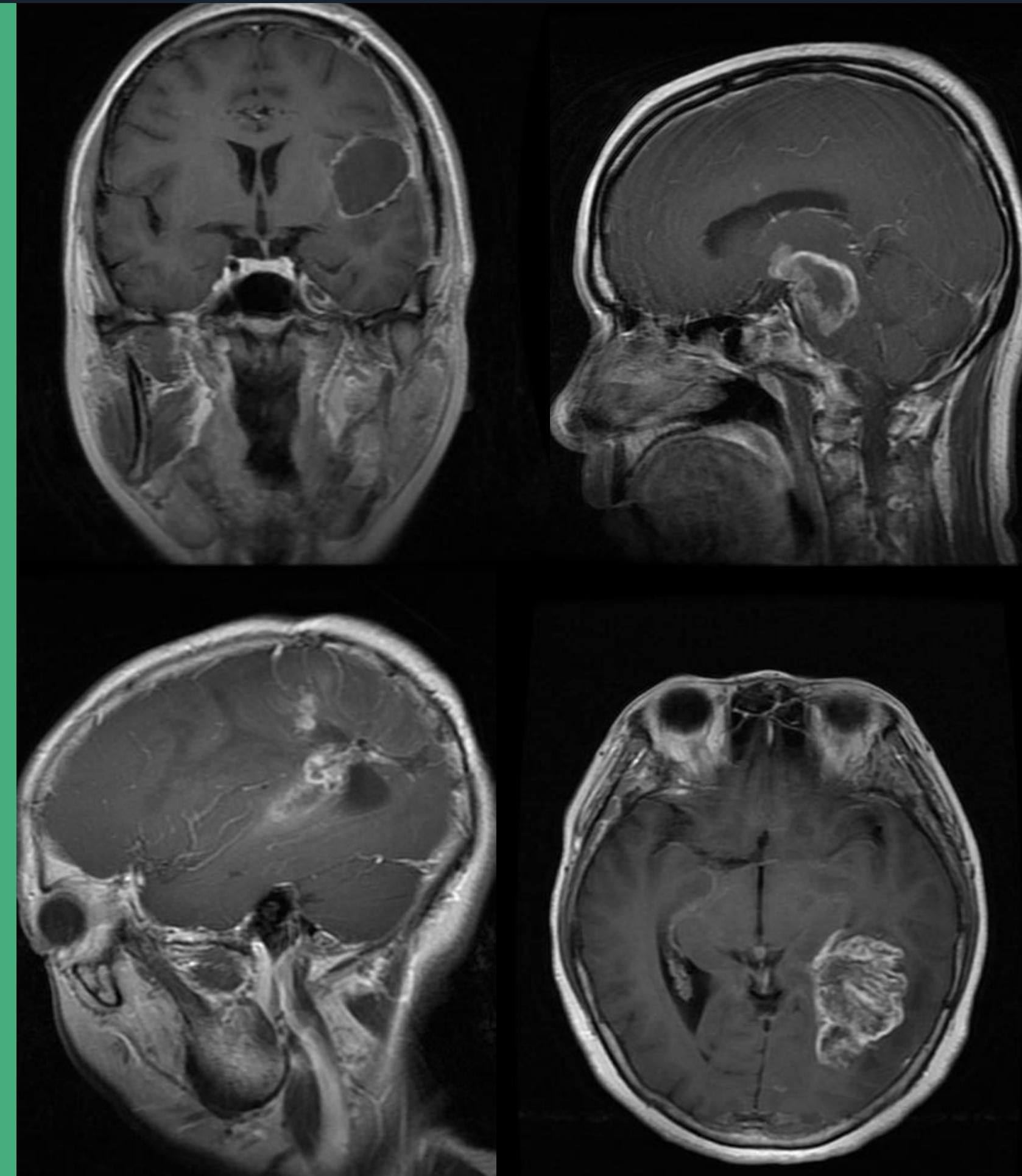


# Transfer Learning

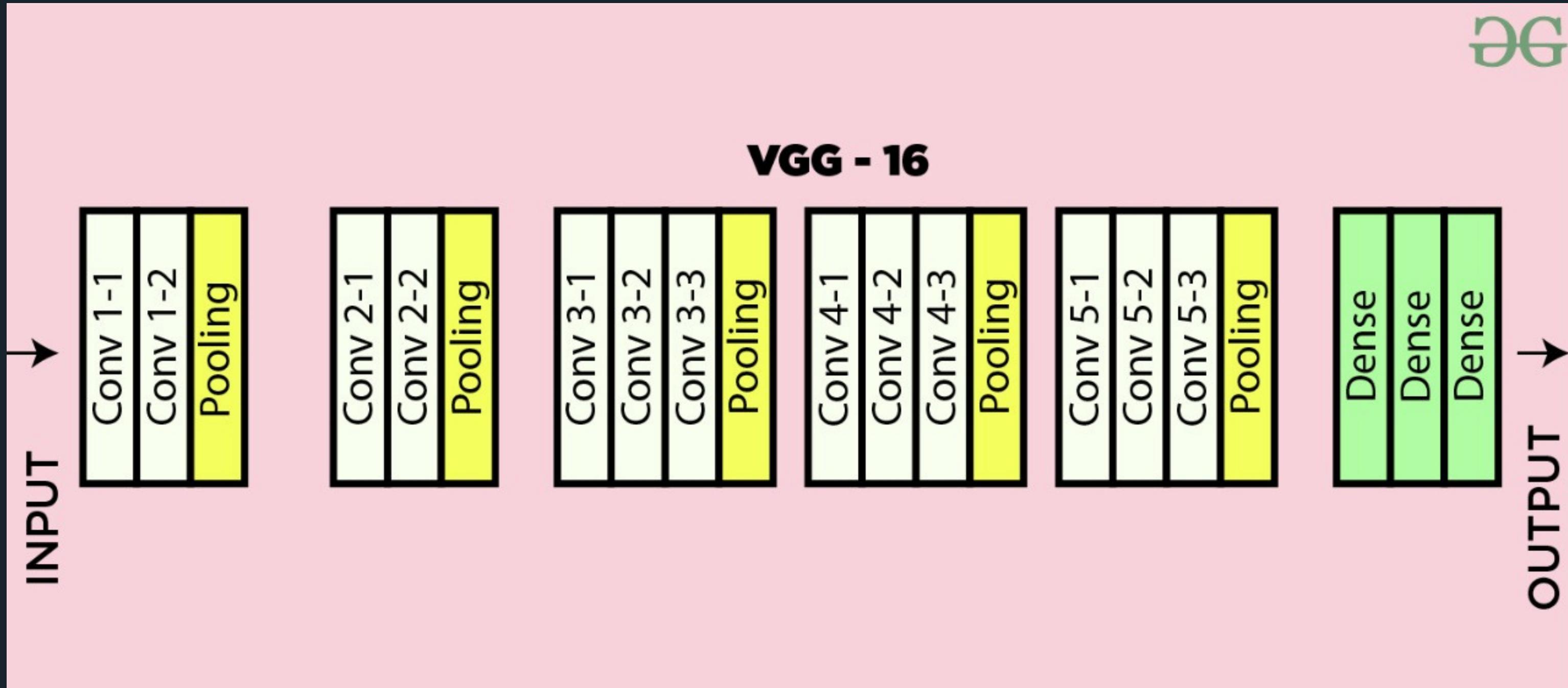
Transfer Learning is when the weights from a previously trained network is used for a different application by just retraining the last fully connected layer with a different output and activation function.



Source: GeeksForGeeks



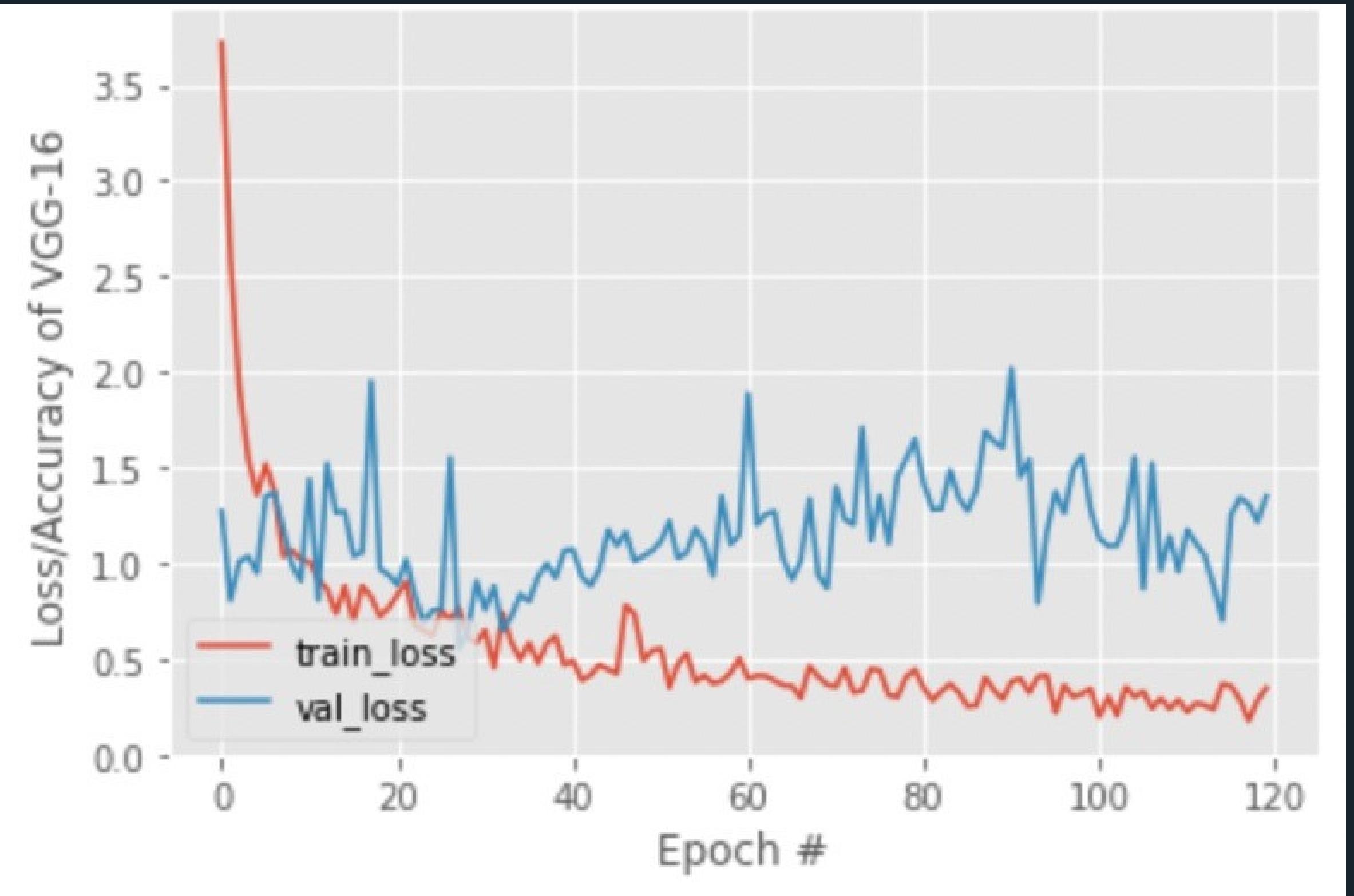
# VGG16



Source: GeeksForGeeks

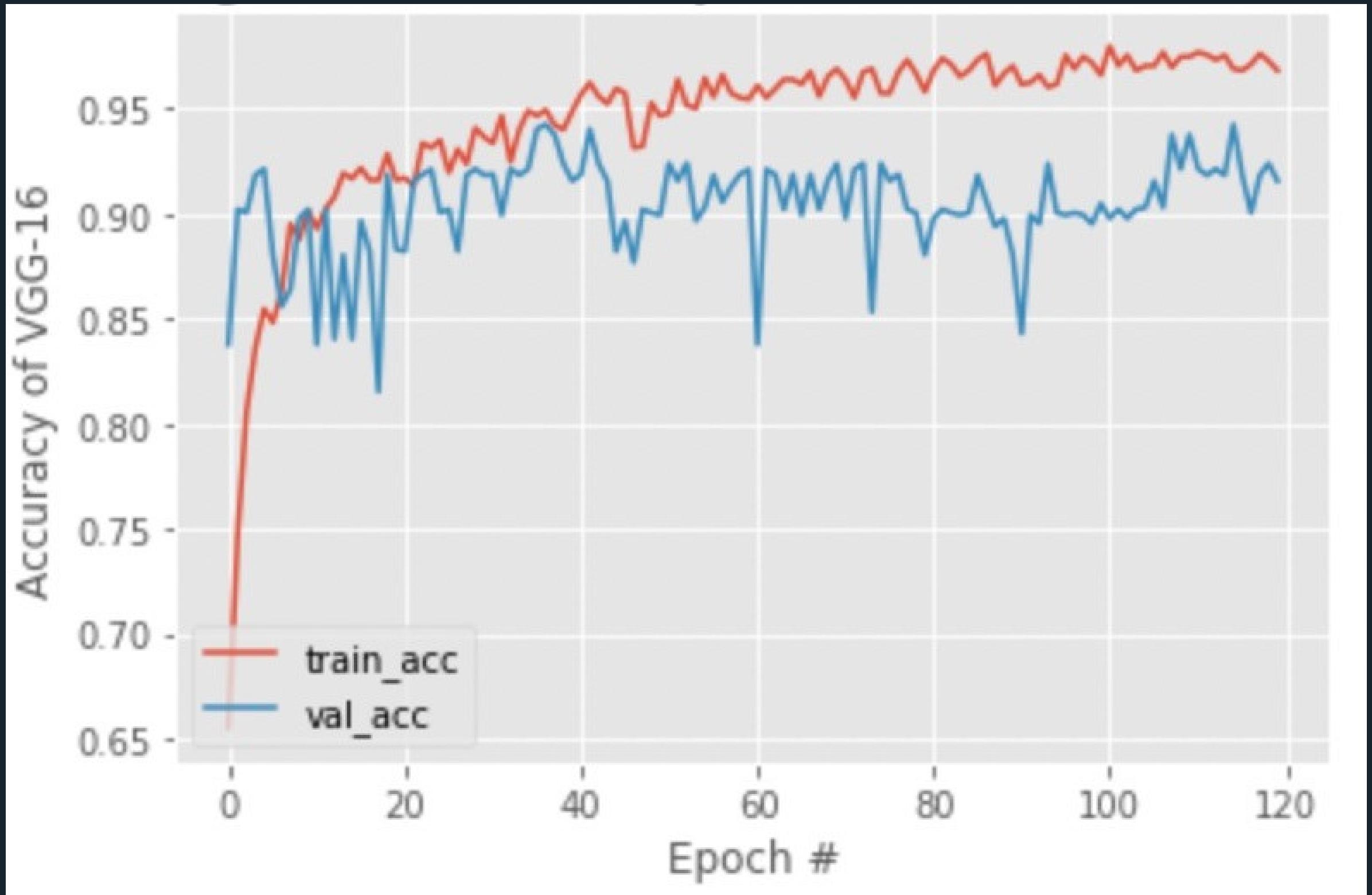
# Loss

## VGG16

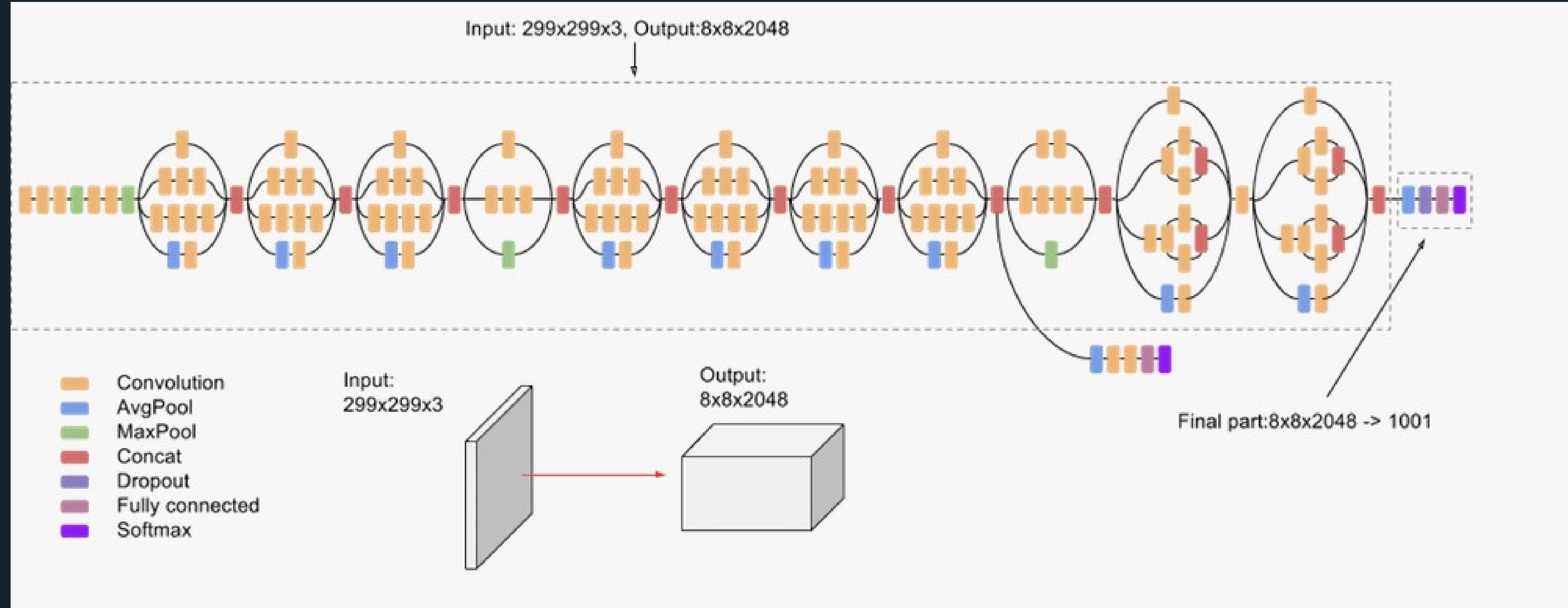


# Accuracy

VGG16



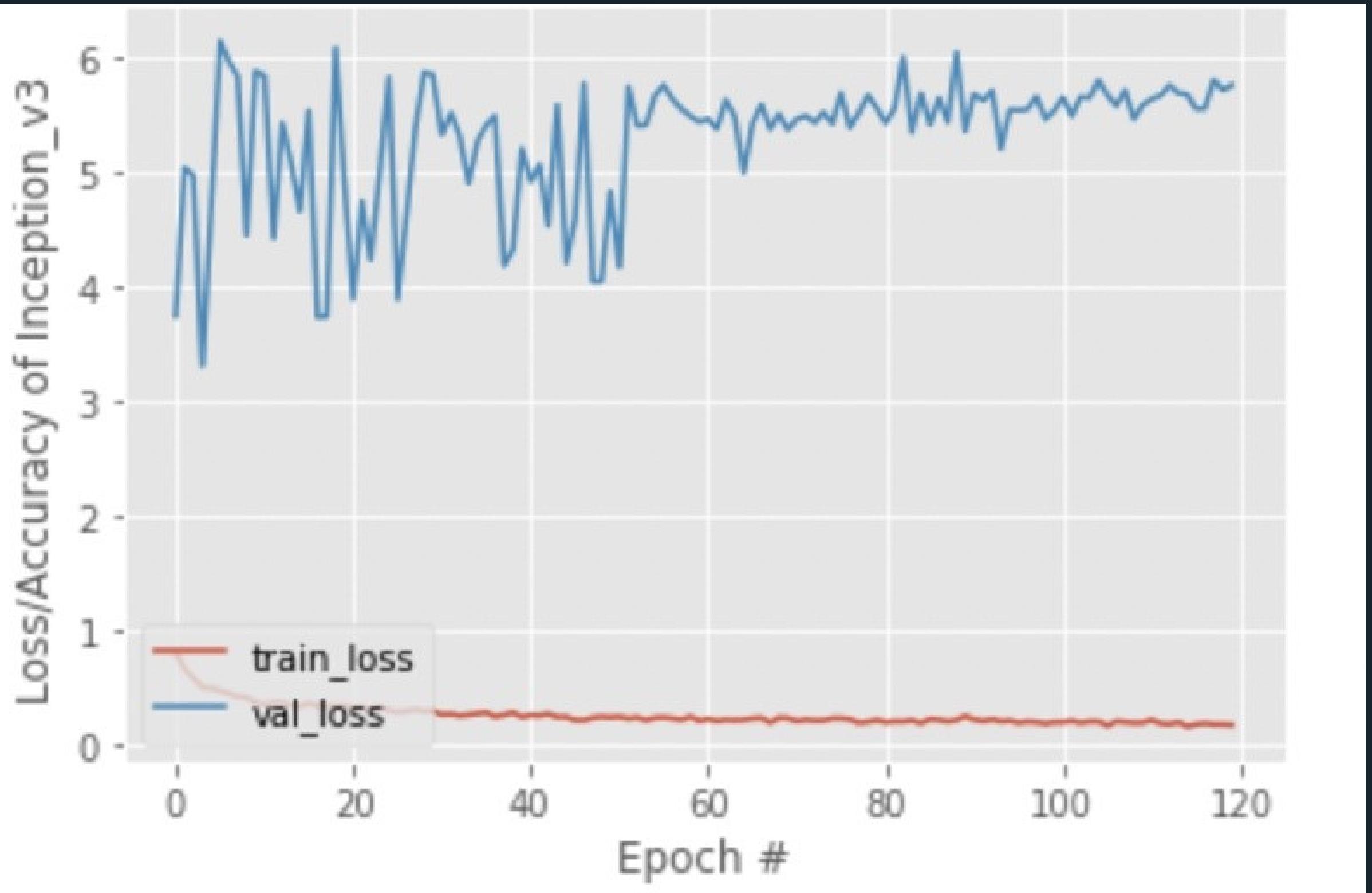
# InceptionV3



Source: GeeksForGeeks

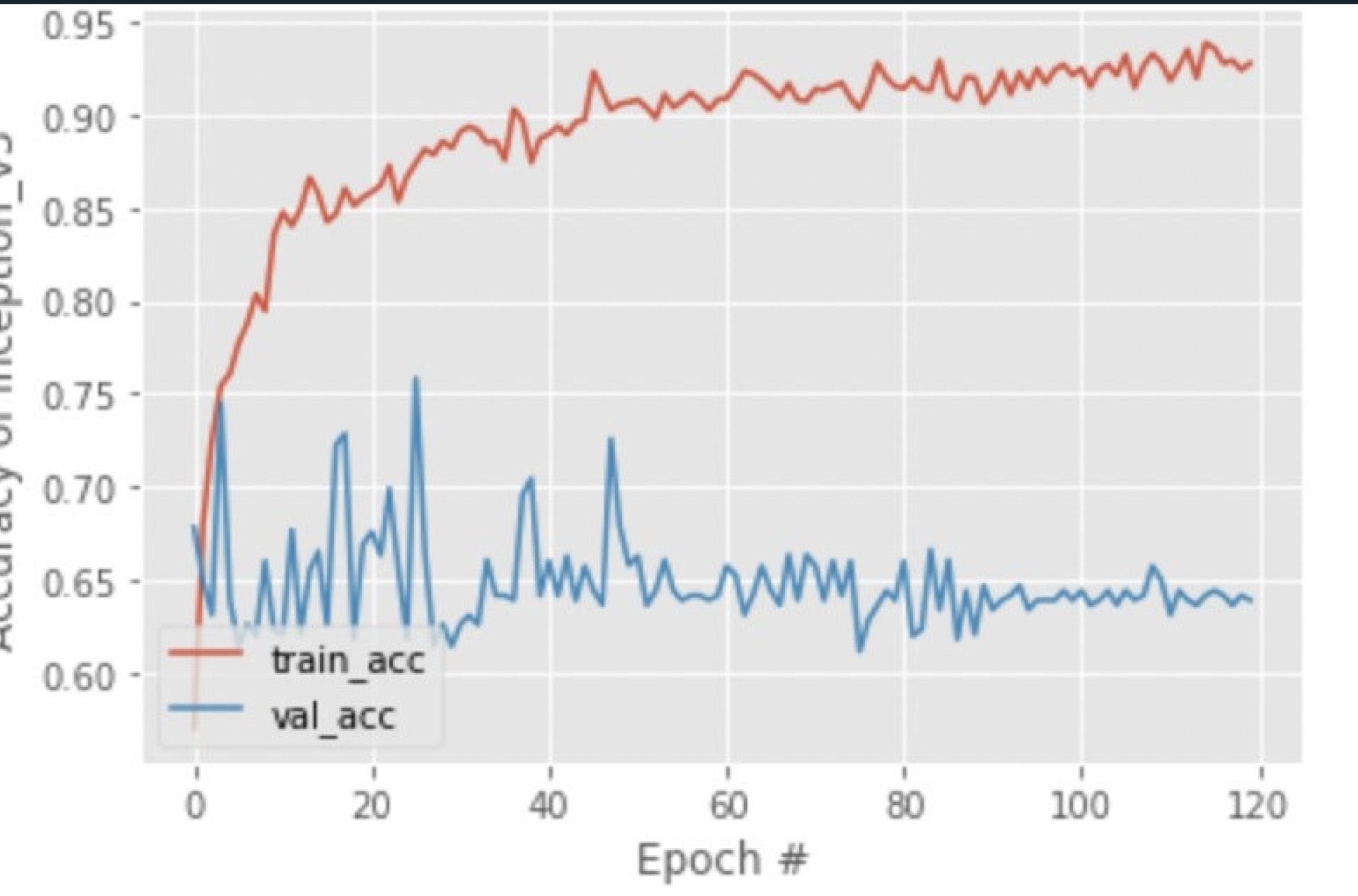
# Loss

## InceptionV3



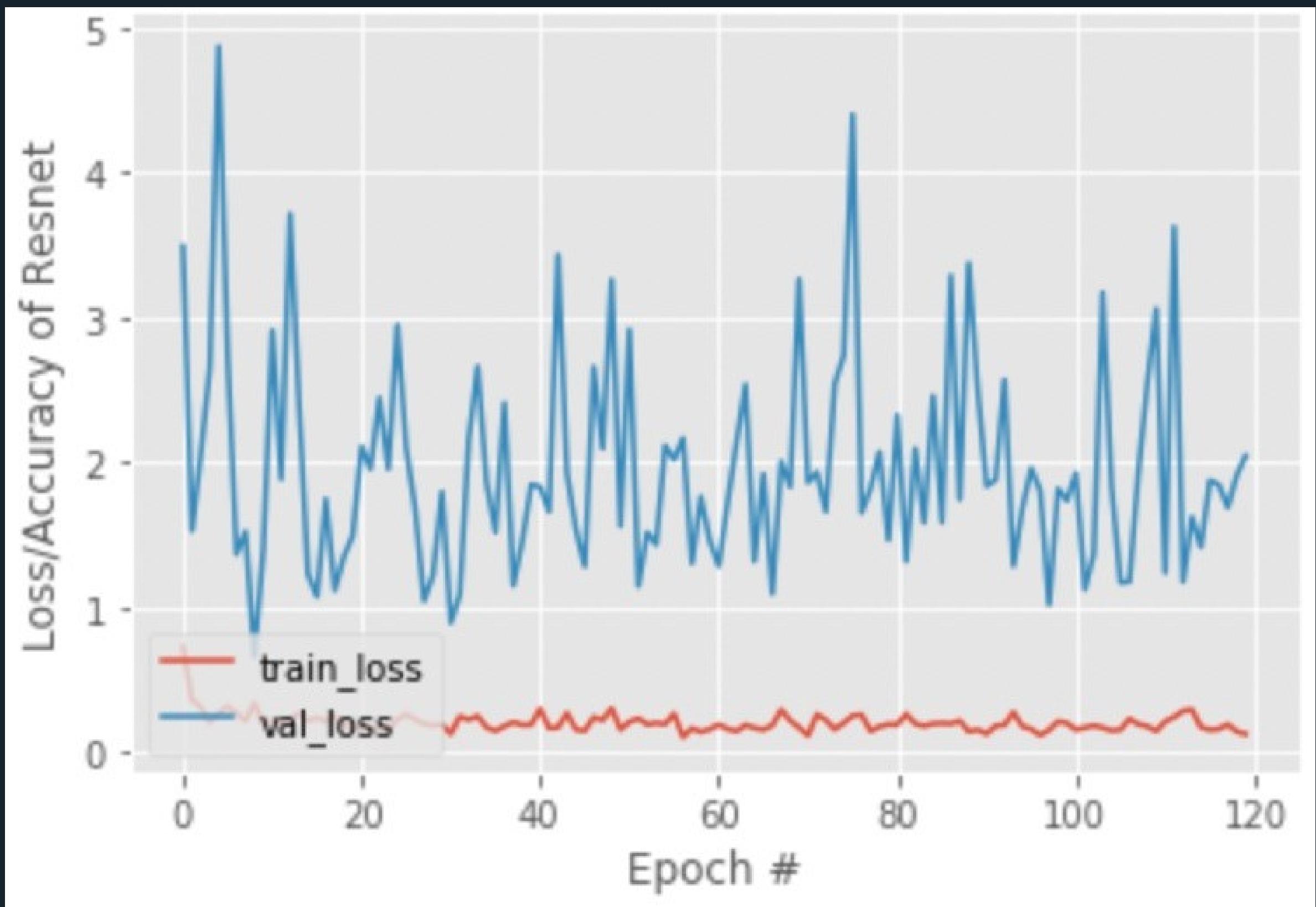
# Accuracy

## InceptionV3



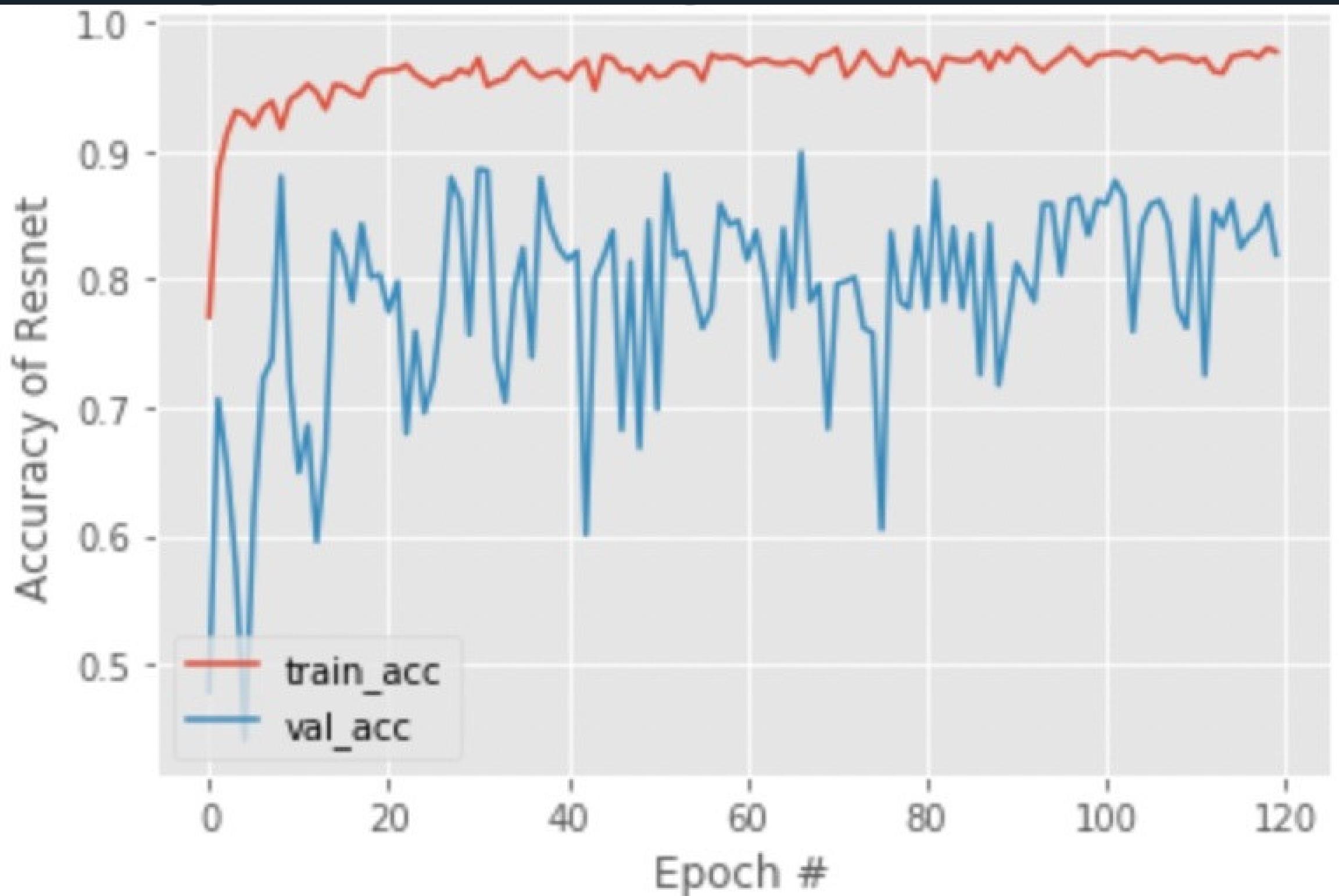
# Loss

Resnet 50



# Accuracy

Resnet 50



# Conclusion

- Though all the models had similar accuracies, the VGG16 model performed the best
- The validation accuracy and test accuracy is higher than the other method.
- Time of computation and computation power is required lesser than traditional method as pretrained weights are used.

