NN/CNN - Brain Tumor Classification

Project Report

Abstract

The brain tumor is one of the most destructive diseases leading to short life expectancy in the highest grade. Of all primary Central Nervous System (CNS) tumors, brain tumors account for 85 to 90 percent. The misdiagnosis of brain tumors will result in wrong medical treatment, which in turn results in reducing the chance of survival. In order to increase the life expectancy of patients, adequate care, preparation, and reliable diagnostics should be introduced. Magnetic Resonance Imaging (MRI) is the best way to identify brain tumors. Through the scans, a huge amount of image data is produced. There are several anomalies in the brain tumor size and location (s). This makes it very difficult to completely comprehend the nature of the tumor. For MRI analysis, a trained neurosurgeon is also needed. The lack of knowledge about tumors also makes it very difficult and timeconsuming to produce MRI studies. An automated system can solve this problem. Application of automated classification techniques using Machine Learning (ML) and Artificial Intelligence (AI) has consistently shown higher accuracy than manual classification. It would be beneficial to propose a method for classification using Deep Learning Algorithms. In the proposed framework, we conduct three studies using three architectures of neural networks, convolutional neural networks (Alex Net, ResNet 50, and VGGNet), to classify brain tumors such as meningioma, glioma, and pituitary and explored transfer learning techniques.

Problem Statement

To build a classification model that can take images of MRI scans as an input and can classify them one of the following types of tumour - glioma_tumor, meningioma_tumor, no_tumor, and pituitary_tumor

Literature Survey

In general, the cancer tumor classification is the segmentation of tumor regions and the classification of the tumor. This vital organ is located in the center of the nervous system. [1]Therefore, tumors that occur in the brain cause life-threatening disease, and, in such cases, early diagnosis is vital. [2]There are only six imaging modalities available to clinicians who diagnose, stage, and treat human cancer: X-ray (plain film and computed tomography [CT]), ultrasound (US), magnetic resonance imaging (MRI), single-photon emission computed tomography (SPECT), positron emission tomography (PET), and optical imaging. Of these, only four (CT, MRI, SPECT, and PET) are capable of three-dimensional (3-D) detection of cancer anywhere in the human body. [3]MRI is used to learn more about cancer such as, the size and location of the tumor, to plan cancer treatments (surgery or radiation therapy), to see how well treatment is working. [4]An MRI is highly adept at capturing images that help doctors determine if there are abnormal tissues within the body. [5]The features to be used for the classification of brain tumors from MRI, play an important role in determining the class to which the tumor belongs.

Application of automated classification techniques using Machine Learning (ML) and Artificial Intelligence (AI) has consistently shown higher accuracy than manual classification, and much work has been done in a similar area as well. Therefore, it would be beneficial to propose a method that performs detection and classification using Deep Learning Algorithms. We reviewed some of the international journals on the detection and classification of brain tumors using deep learning. We analyzed that various available deep learning algorithms like Convolutional Neural Networks (CNNs), long Short Term Memory Networks (LSTMs), Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GANs), Radial Basis Function Networks (RBFNs) etc can help to learn specific type of data for classification or grouping. For given brain MRI scans, the specific task is to classify the types of tumour, as given in the problem statement. The provided dataset doesn't have any volumetric MRI scans, like used in real time brain tumour diagnostics. So we can say that the input data is independent and invariant of time. For such database the best deep learning algorithm would be Convolution neural networks (CNNs).

[6]Muhammad Sajjad presented an approach of classifying multi-grade tumors by applying data augmentation technique to MRI images and then tuning it using a pre-trained VGG-19 CNN Model. [7]Carlo, Ricciardi, suggested the classification of pituitary adenomas tumor MRIs using multinomial logistic regression and k-nearest neighbor algorithms. The method achieved 83% accuracy on multinomial logistic regression and 92% accuracy on a k-nearest neighbor with an AUC curve of 98.4%. [8]Arshia Rehman used three different pre-trained CNN models- VGG16, AlexNet, and GoogleNet, to classify the brain tumors into pituitary, glioma, and meningioma. Among these three transfer learning models, VGG16 acquires the highest accuracy, that is, 98.67%. [9]Ahmet Cinar modified the pre-trained ResNet50 CNN model by removing its last five layers and adding eight new layers instead and comparing its accuracy with other pre-trained models such as GoogleNet, AlexNet, ResNet50. The updated ResNet50 model achieved 97.2% accuracy. [10]Dr. D. Stalin David showed in his study that the over classification of brain tumor accuracy of the proposed method is 97.73, ResNet50 is 95.62, DenseNet121 is 96.22 and 95.91. [11]As mentioned by M. Yildirim in his paper, Densenet201 correctly classified 36 of 36 normal images. In addition, he predicted 25 of 31 brain tumor images correctly, and 6 predicted brain tumor images incorrectly with 91.04% accuracy rate while training the model and in addition 88.06% accuracy rate was obtained while training the network with Inceptionv3 model. [12]Nada M Elshennaway researched on a similar project on pneumonia that gave accuracy of 91% by

MobileNetV2 and 99.22% by ResNet152V2. ALI M. HASAN were able to classify thebrain tumor by 77.80% using model SqueezeNet. [13]In a paper ResNet-Inception-v2 was also mentioned as a useful that gave 93.67% classification accuracy for 25 epochs.

After analyzing various literature, it can be inferred that different pre-trained CNN Models using the transfer learning is the most effective approach to classify brain tumors. Most of the literature addresses the classification efficiency using the transfer learning approach.

Data Description and Analysis

The dataset contains 2881 train and 402 test MRI scanned grayscale images that further falls into four categories:

- Glioma tumour - Tumour that occurs in the brain and spinal cord
- Meningioma tumour - Tumour that arises from the membranes surrounding the brain and spinal cord
- No tumour - There is no tumour in the brain
- Pituitary tumour - Tumour in the pituitary gland that doesn't spread beyond the skull

After analyzing the provided Data, the partition for the training and testing data set is presented visually in Figure 1. and Figure 2. respectively. The number of images in the training dataset is fairly distributed, so the dataset does not require any sampling methods to be applied. Additionally the images are Linearly independent and Time variant.

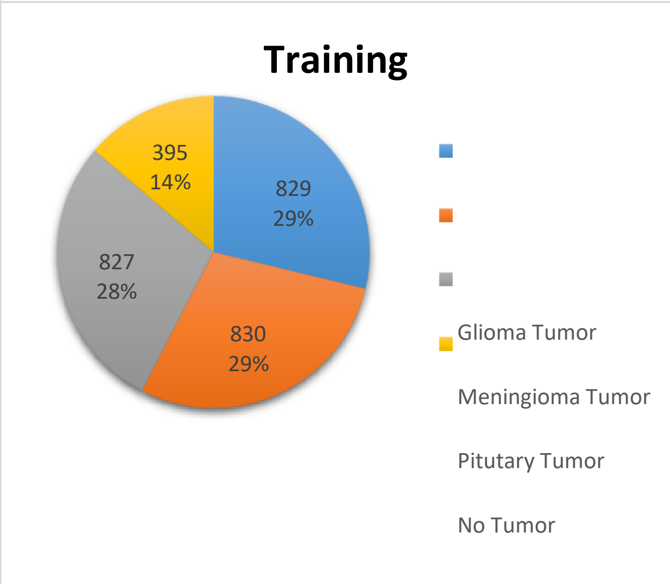


Figure 1. Analysis of Training Dataset

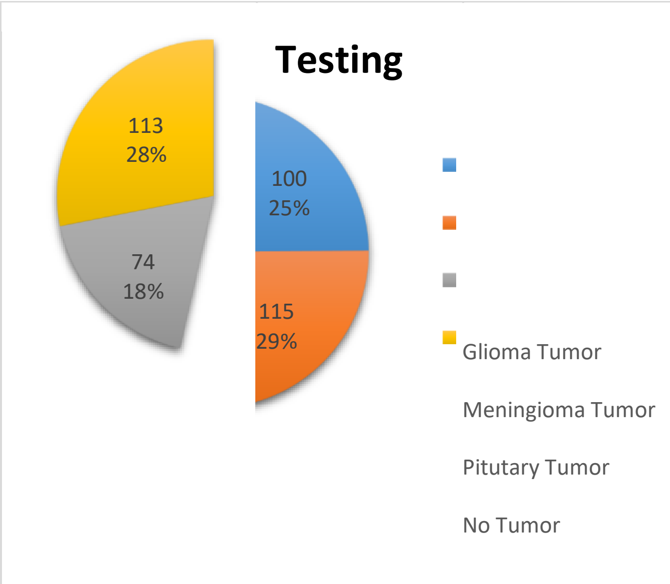


Figure 2. Analysis of Testing Dataset

Data Preprocessing

Before building a model on the provided data, we preprocessed it by applying the following steps.

1. Reading the images from all four folders and storing them in the array, separately as training and testing data
2. Reshaping the images to a particular pixel to maintain the same size. The pixel size used for each model is mentioned in the Table 1
3. To convert the range of grayscale images from 0-255 to 0-1, each image was divided by 255
4. One-Hot Encoding of Test Images so that the output could be evaluated

Pixel Size	Transfer Learning Model
150×150	VGG16
192×192	squeezenet
224×224	DenseNet121, DenseNet201, EfficientNetB0, EfficientNetB2, MobileNetV2, NASNetMobile, ResNet50, ResNet101, ResNet152V2, VGG19
227×227	Alexnet
256×256	InceptionResNetV2
299×299	InceptionV3, Xception
331×331	NasNetLarge

Table 1. Pixel size of different transfer learning models

ANN

Various authors adopted artificial neural networks (ANNs) to optimize multipurpose parameters. In most cases ANN allows to predict the properties of the dataset or model. In our study we used different ANN model and the compared them. Initially we created a shallow layer network with 2 layers and then further.

ANN : Shallow Layer	ANN : Deep Layer	ANN : Optimised
ANN Network : 2 Layers – 2DL + 1O/p L 150x150x1 pixel gray images	ANN Network : 4 Layers – 4DL + 1O/p L 150x150x1 pixel gray images	ANN Network : 6 Layers – 4DL + 2RegLayer 150x150x1 pixel gray images
L1 : D1 – 50	L1 : D1 – 150	L1 : D1 – 150
L2 : D2 – 20	L2 : D2 – 100	L2 : R1 – Dropout 20%
L3 : O/p L – 4	L3 : D3 – 50	L3 : D2 – 100
	L4 : D4 – 20	L4 : R2 – Dropout 20%
	L5 : O/p L – 4	L5 : D3 – 50
		L6 : D4 – 20
		L7 : O/p L – 4

Table 2. Comparison between different ANN models

CNN

CNN is a class of deep neural networks, applied to analyzing visual imagery. CNNs are regularized versions of multilayer perceptions (fully connected networks) in which each neuron in one layer is connected to all layers in the next layer. We made a basic model initially as given in Figure 1. To get the better validation accuracy, we started adding a few more layers to it. After attempting multiple iterations, we were able to achieve 76.62% accuracy by using the layers mentioned in Figure 2.

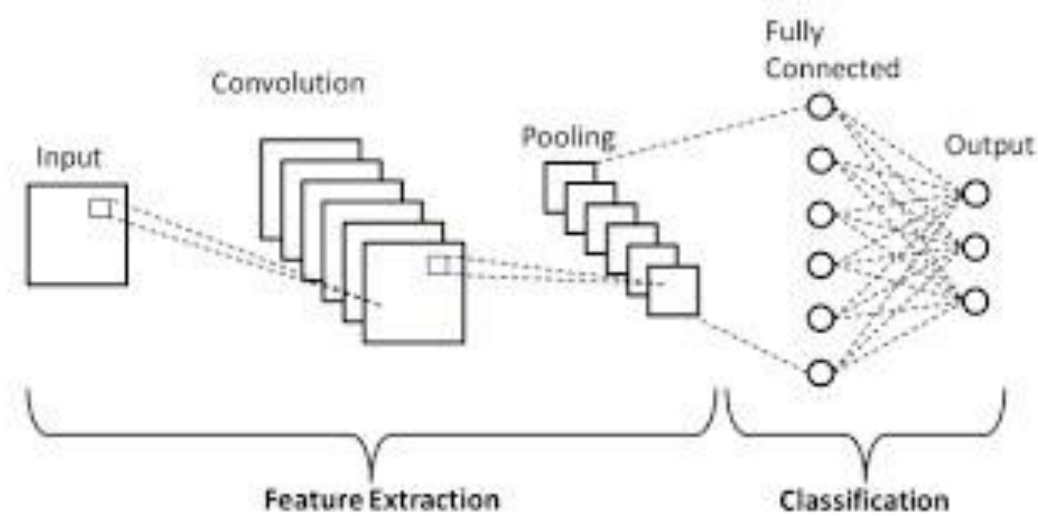


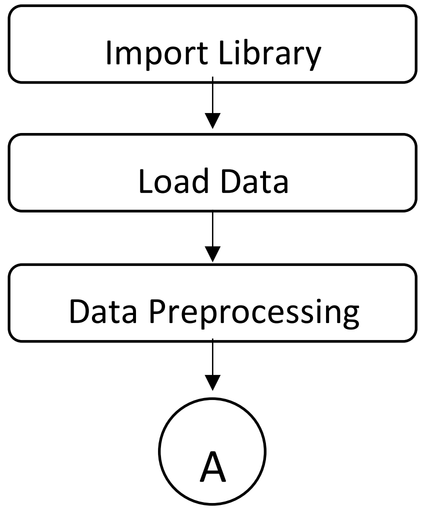
Figure 3. Basic CNN model architecture

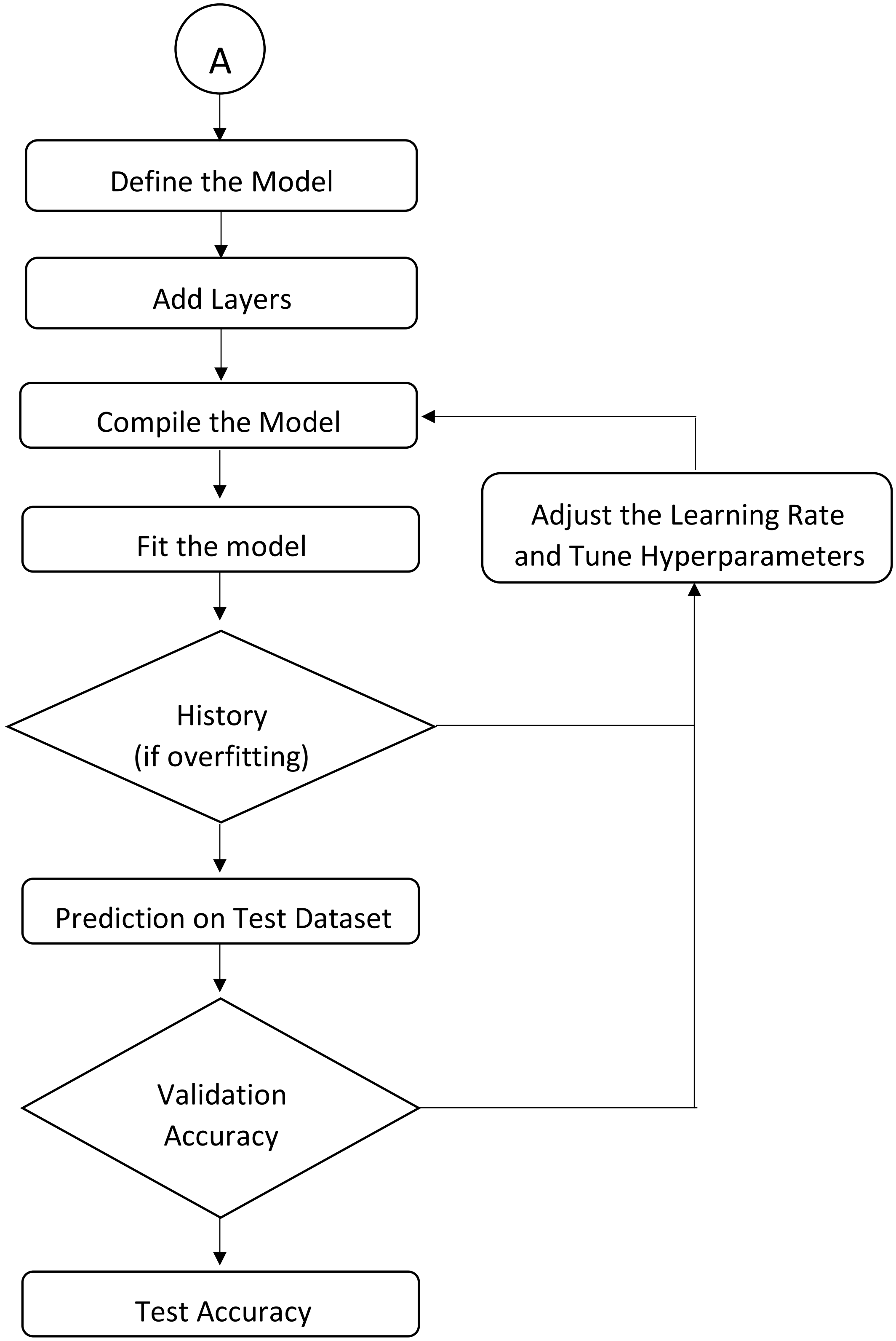
Layer	No of Layers
Input Layer	1
Conv Layer	3
Batch Normalization	1
Max Pooling	1
Dropouts	2
Activation Function	1
Flatten Layer	1
Dense Layer	3
Including Output Layer	

Table 3. Layers of customized CNN

As mentioned in many literatures, transfer learning models are used to maximize the accuracy. In transfer learning approach, instead of making a scratched CNN model for the image classification problem, a pre-trained CNN model that is already modeled on a huge benchmark dataset is reused.

Flow Chart





Flow chart for the basic CNN model is giver above.

Transfer Learning Model

Sinno Pan and Qiang Yang have introduced a framework for a better understanding of Transfer Learning. Instead of starting the learning process from scratch, the transfer learning leverages previous learning. In our study, we tried 20 different transfer learning models, among which the 14 models gave descent accuracy which were VGG19, DenseNet121, DenseNet169, MobileNet, MobileNetV2, NASNetMobile, InceptionResNetV2, DenseNet201, ResNet152V2, ResNet50, ResNet101V2, ResNet101, ResNet152, ResNet50V2. The heatmap of these models is given in the appendix. The other implemented transfer learning models were EfficientNetB0, EfficientNetB1, EfficientNetB2, EfficientNetB3, EfficientNetB4, NasNetLarge, VGG16, InceptionV3, and AlexNet which had lower accuracy. Their results are shown in the appendix. Further, the accuracy of these models was increased by tuning the hyperparameters. Among all the models ResNet101V2 was giving the highest accuracy that was 82.09.

Misclassification

Basic CNN structure was not able to classify images upto a certain point. However, we were able to get better results with Transfer learning model, specifically ResNet101V2. The Figure 3 clearly shows that 3 classes, Meningioma_tumor, Pituitary_tumor, and no_tumor are fairly classified. But the glioma tumor is misclassified as meningioma tumor and no tumor. There is still a scope of improvement for the model. Heatmap for the other model is given in the appendix.

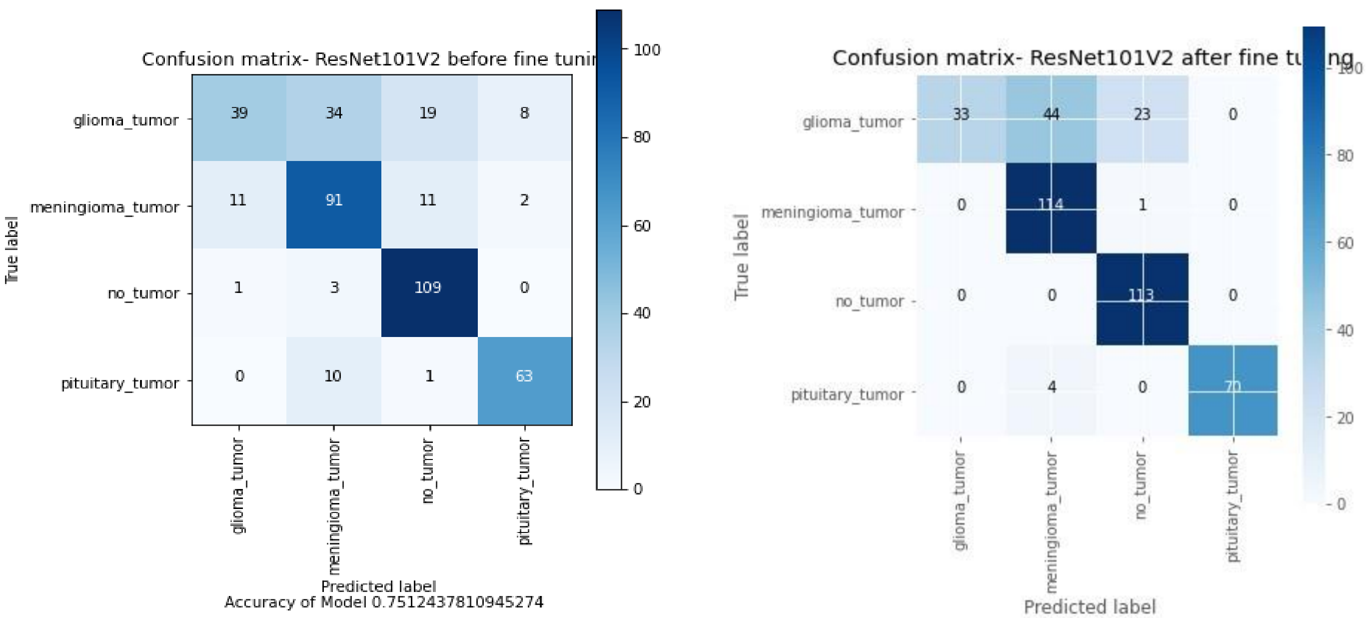


Figure 4

Future Scope

1. Diseases that could be addressed using the same CV Methods
    a. Autism Spectrum Disorder
    b. Depression / Bipolar Disorder
    c. Alzheimer Disease
    d. Pneumonia
2. Using different Datasets Weights than Imagenet
3. Volumetric MRI Scans
    a. To accommodate Diagnosis procedure followed by Radiologist

b. Deep Learning with Time Series - LS
4. Other Technical Approaches
    a. More number of MRI Scans
    b. More computing power for example more GPUs and TPUs

Conclusion

1. Basic CNN Model gave 76.62% accuracy.
2. Multiple Transfer Learning Models have been implemented to compare the outcome
3. 14 models had good accuracy among all the models we applied.
4. Maximum validation accuracy before tuning is 79% for DenseNet201
5. After tuning the transfer learning models, maximum accuracy is 82.09% for ResNet101V2.

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[13] L. I. E. P. Ilias Maglogiannis, "Transfer Learning Using Convolutional Neural Network Architectures for Brain Tumor Classification from MRI Images," *Nature Public Health Emergency Collection,* pp. 189-200, 2020.

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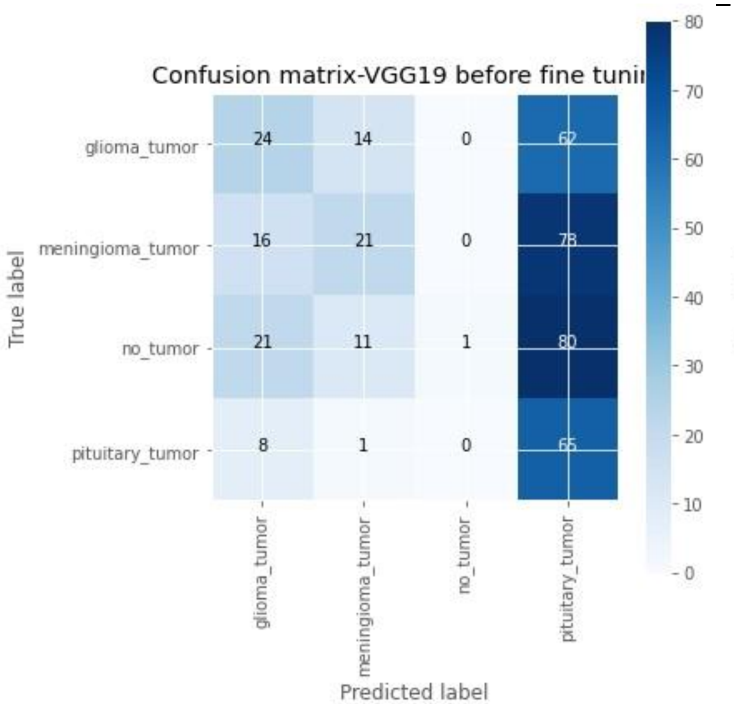
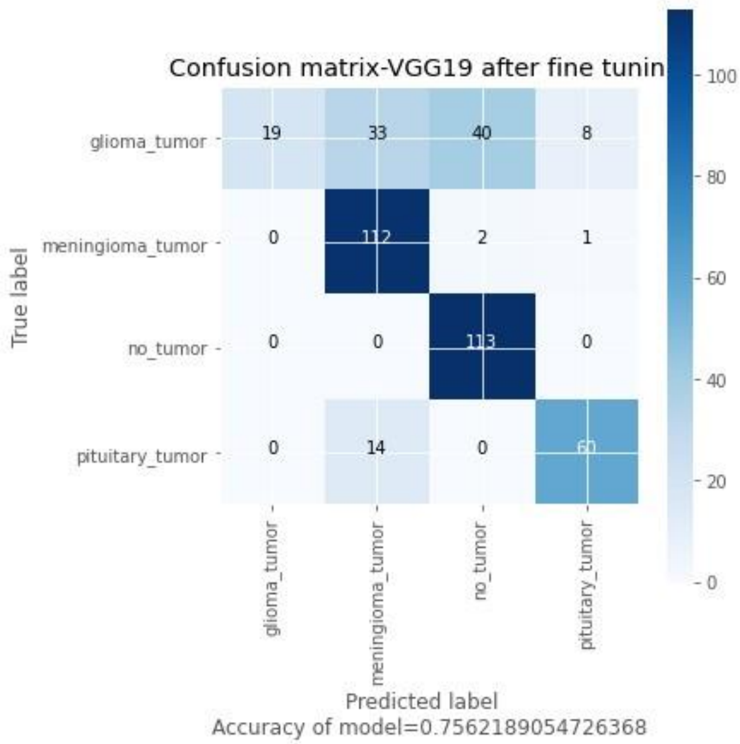
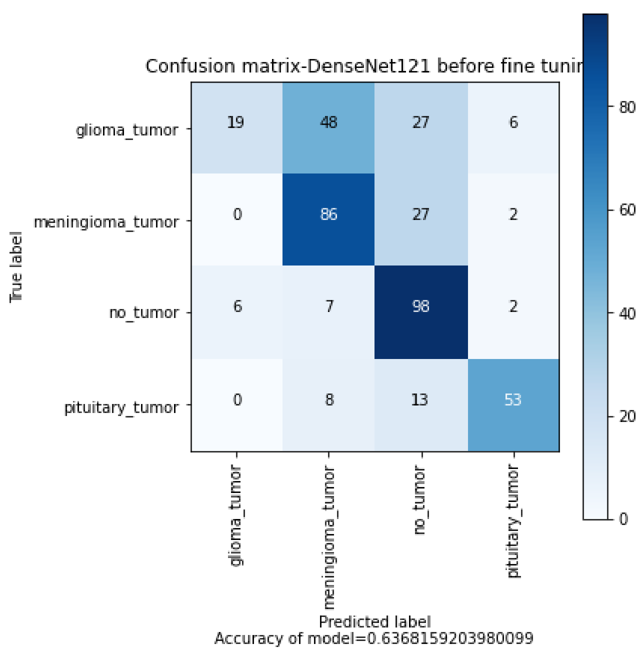
Appendix

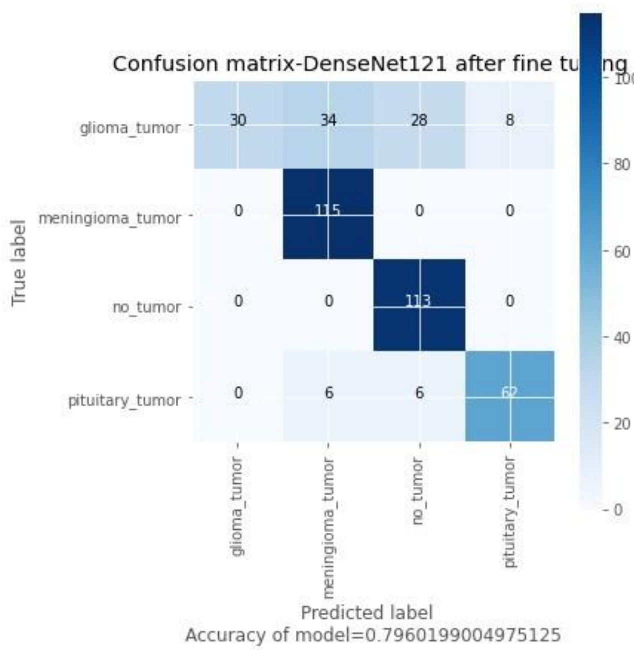
VGG19





DenseNet121





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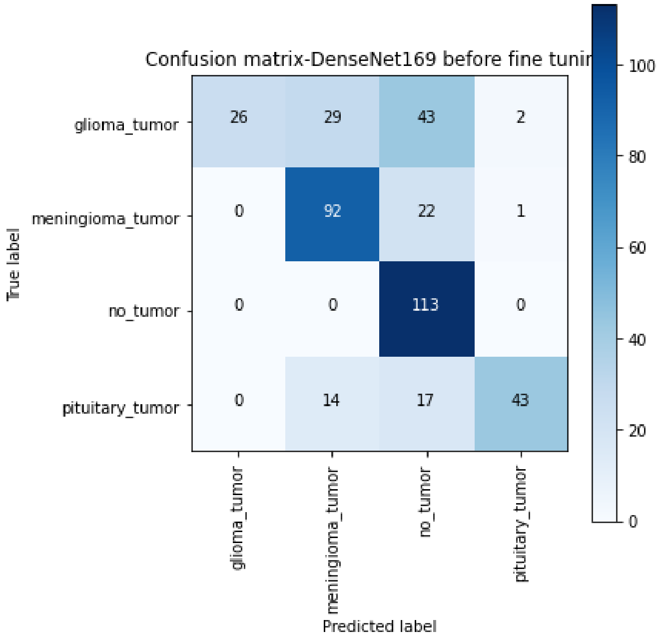
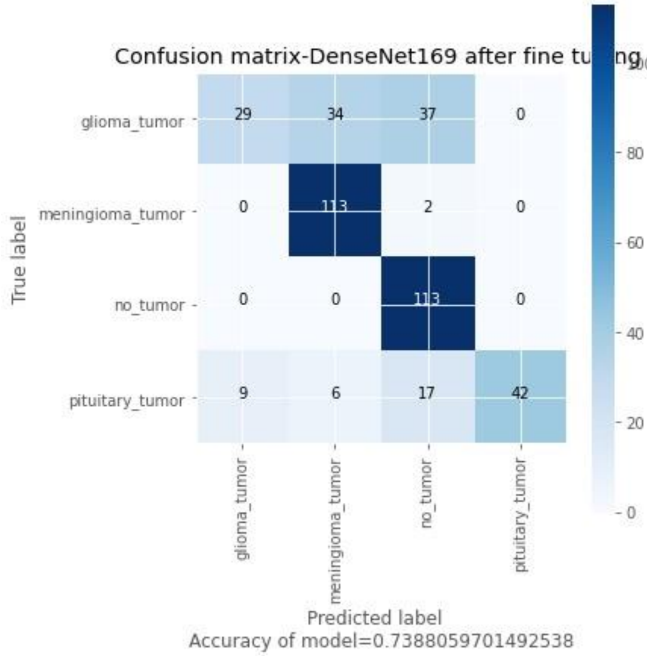
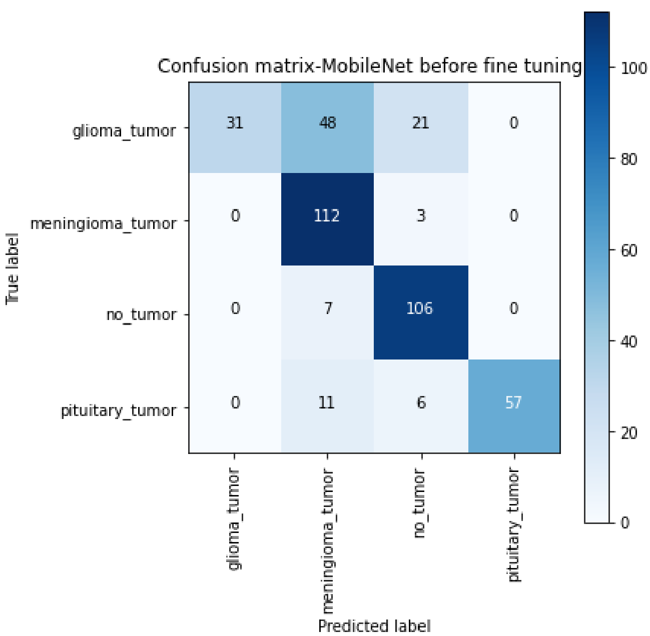
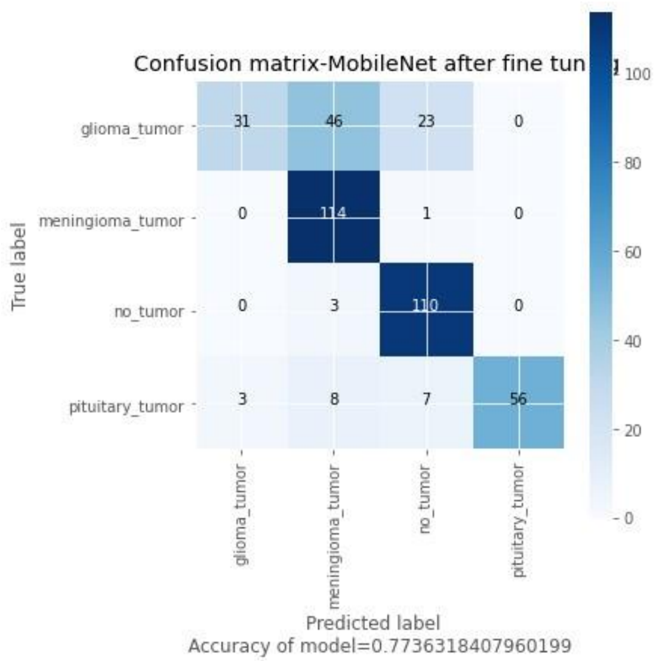


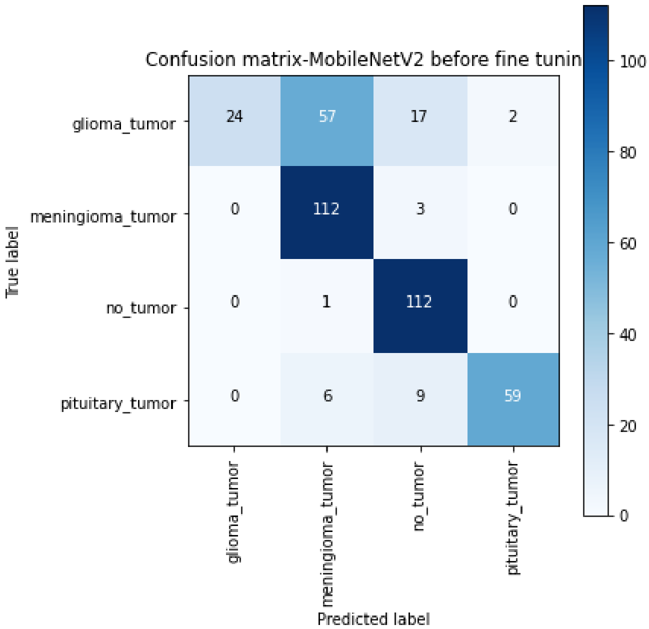


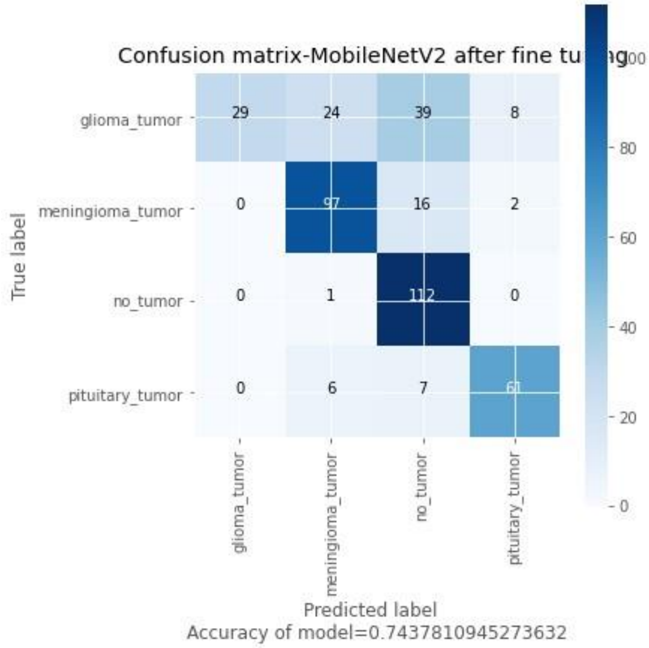
MobileNet



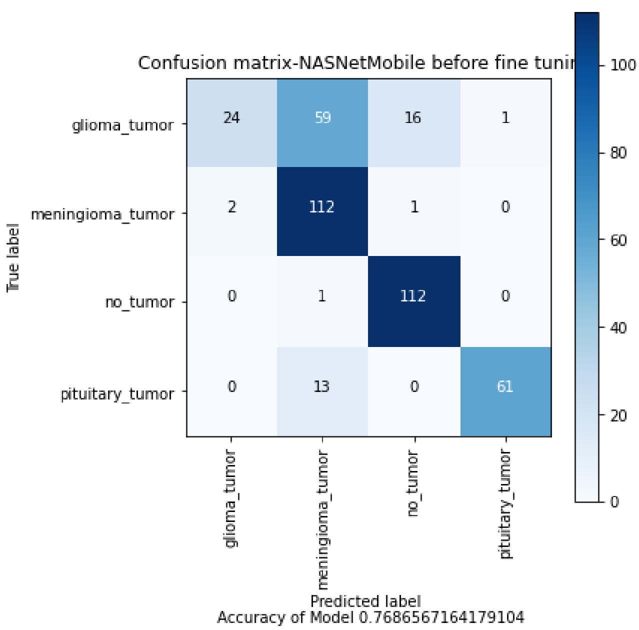


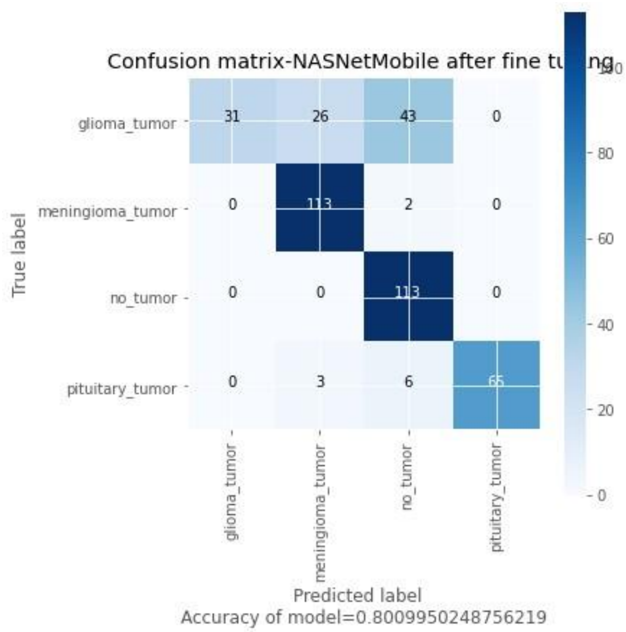
MobileNetV2





NASNetMobile





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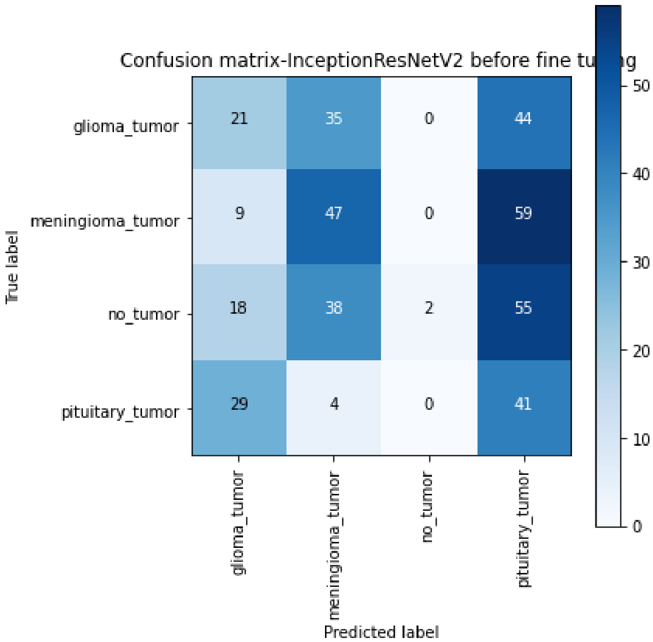

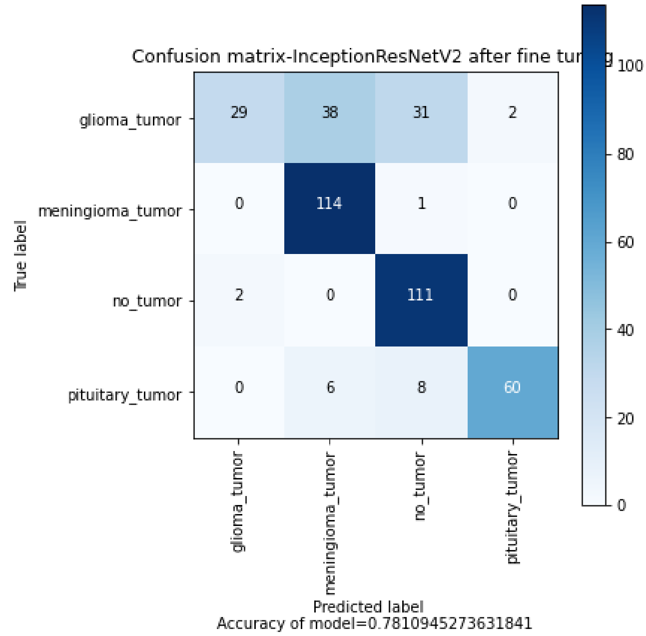

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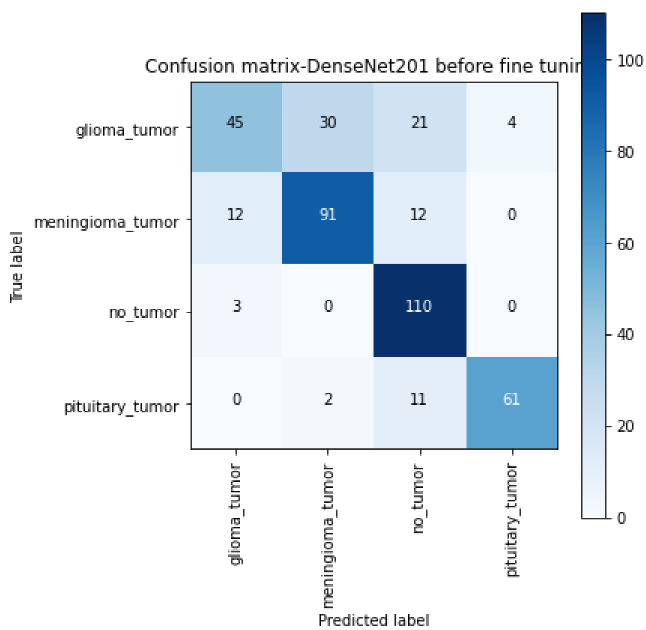

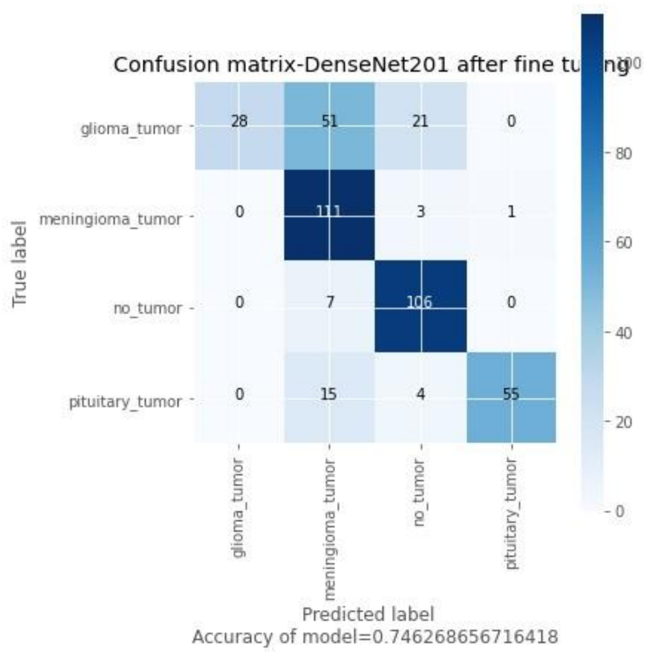

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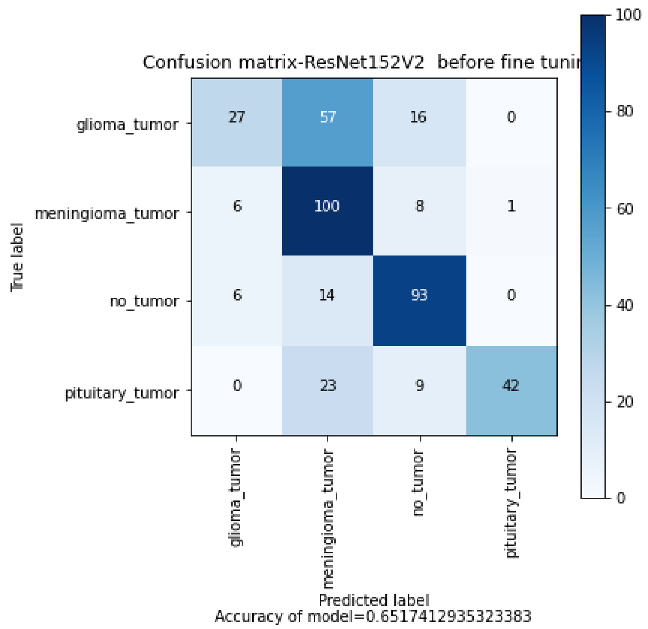

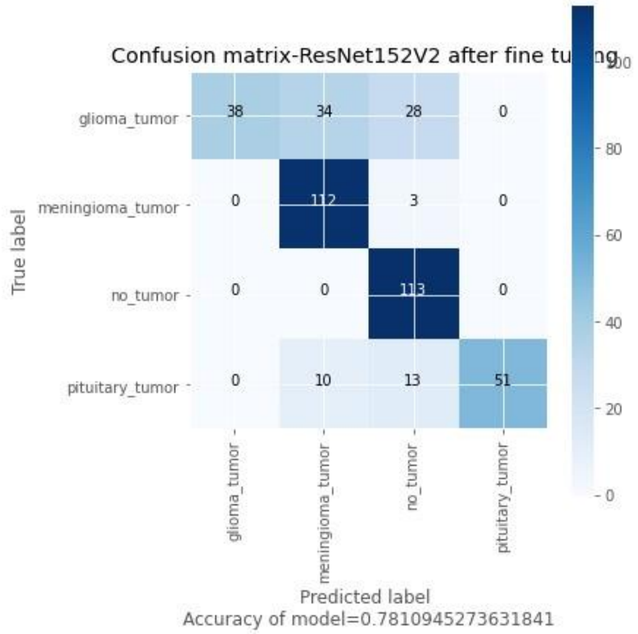

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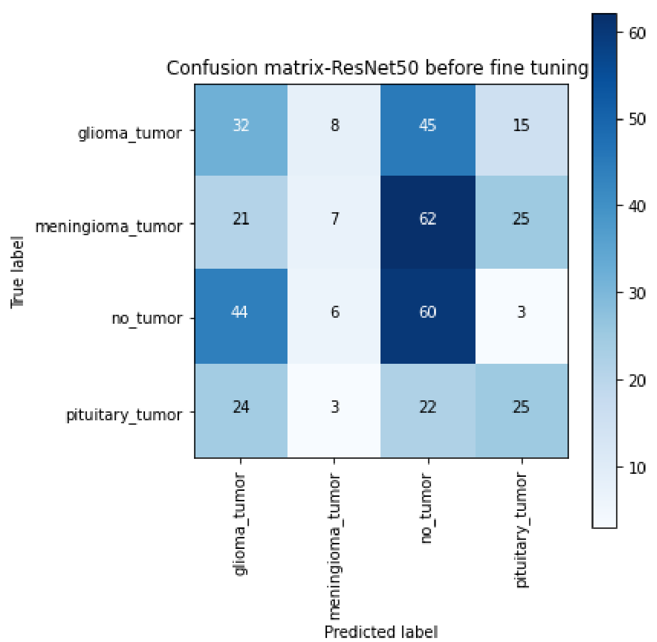

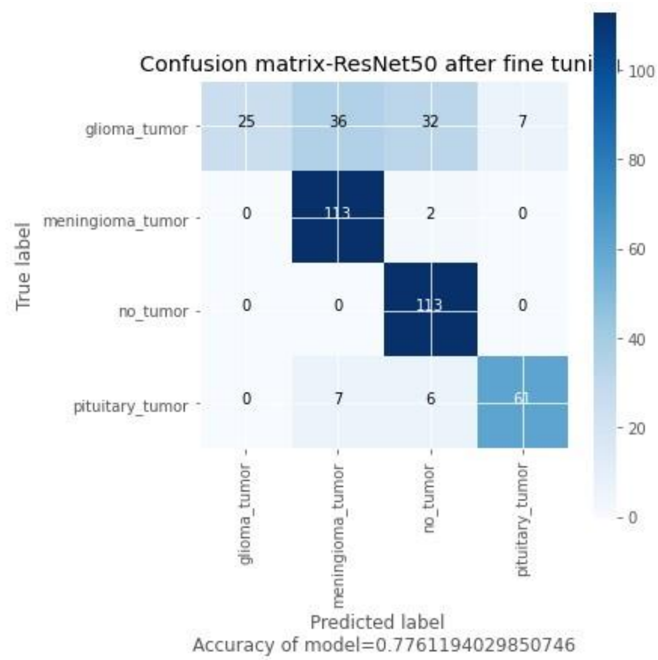

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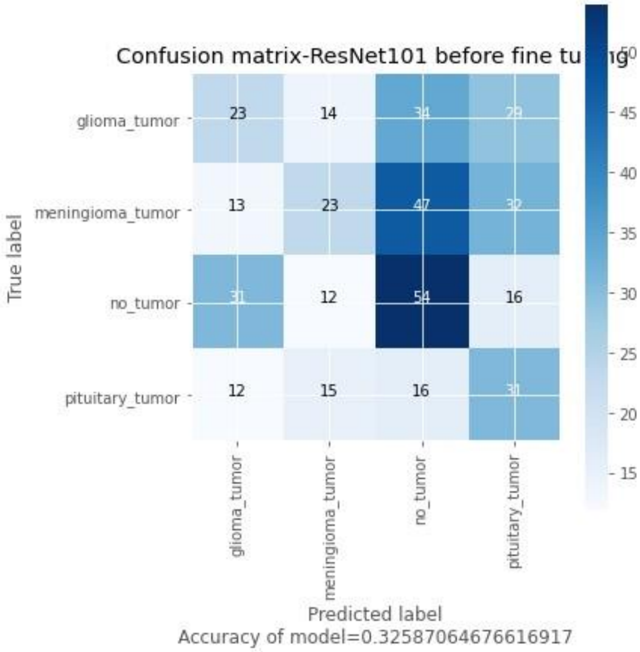
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no_tumor
pituitary_tumor
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Predicted label
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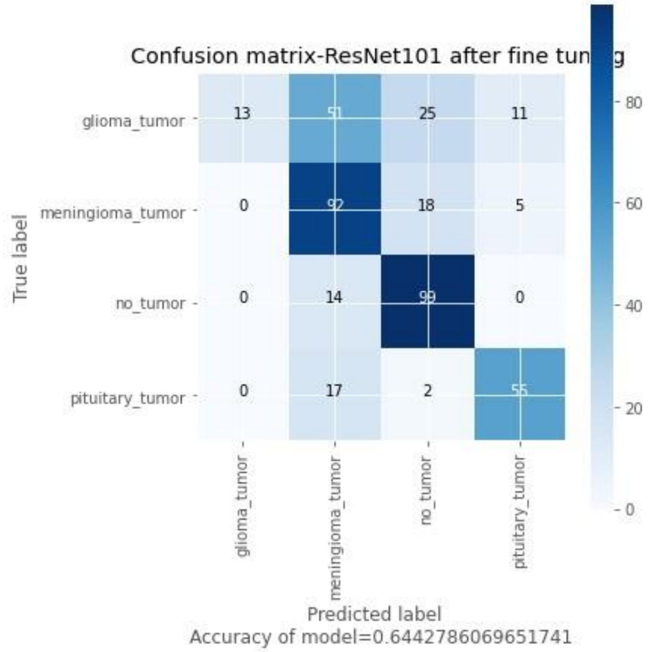
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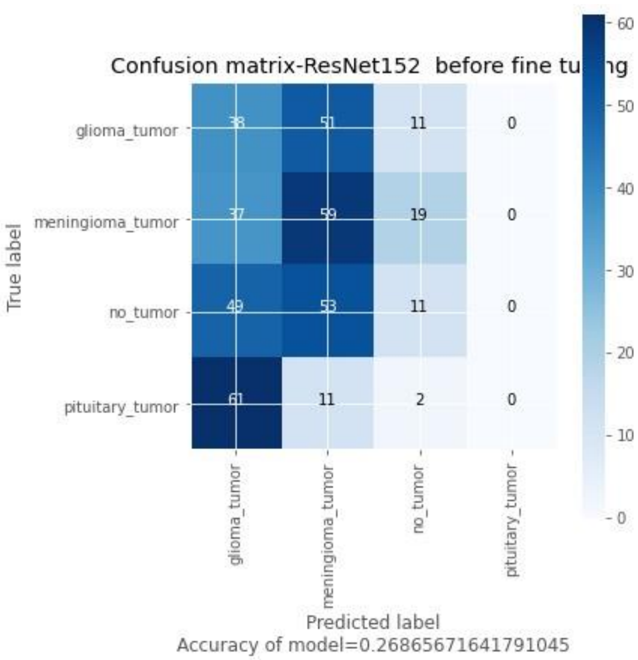
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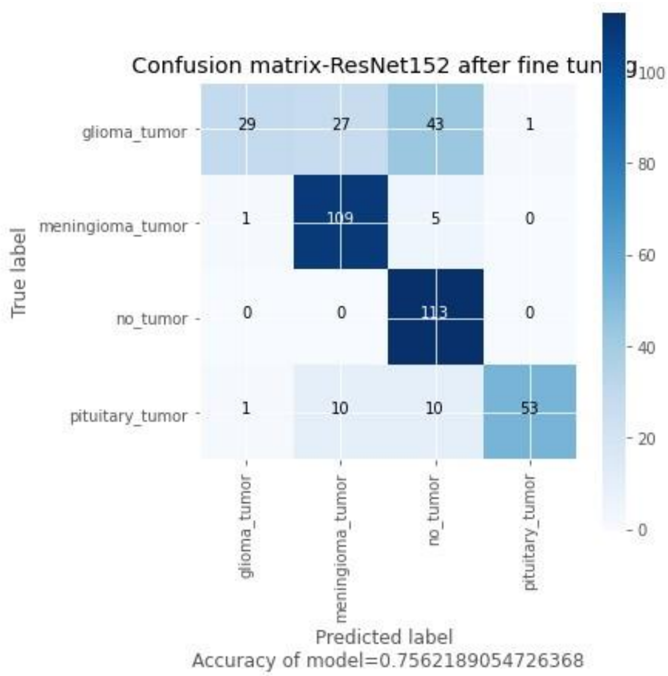
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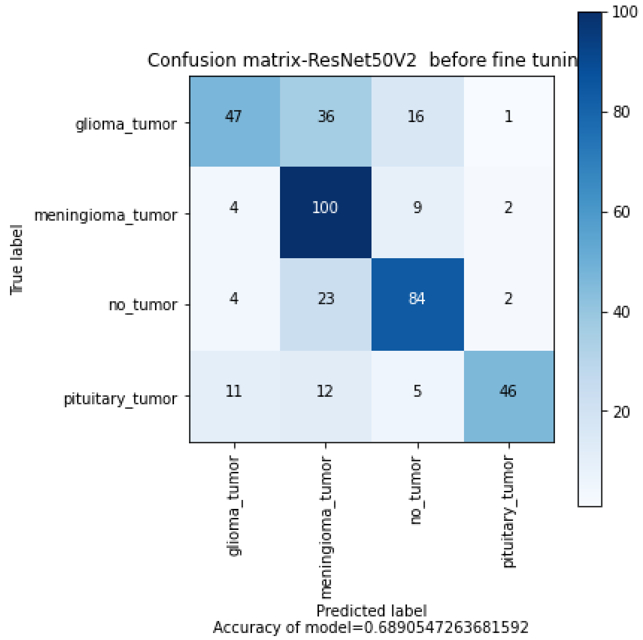
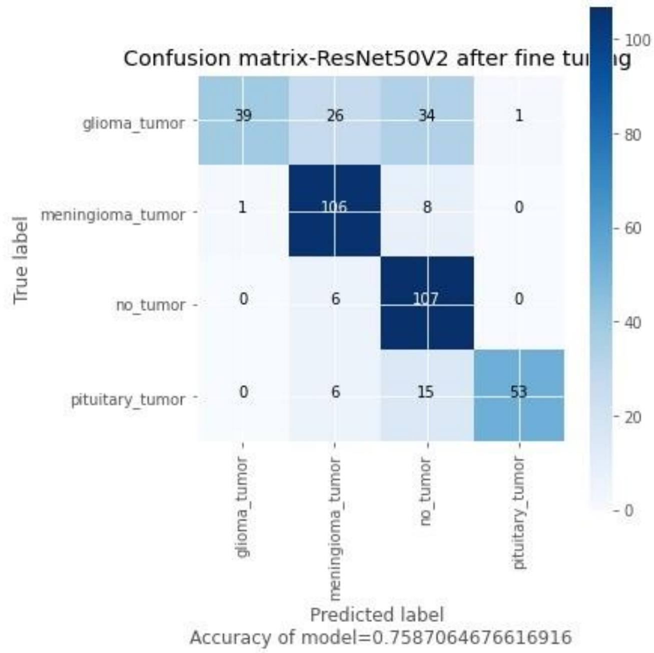
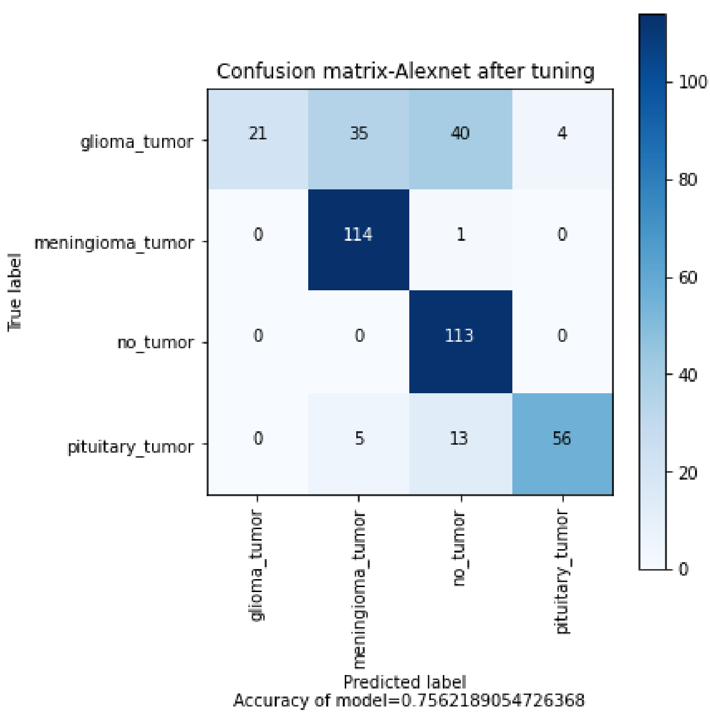




AlexNet



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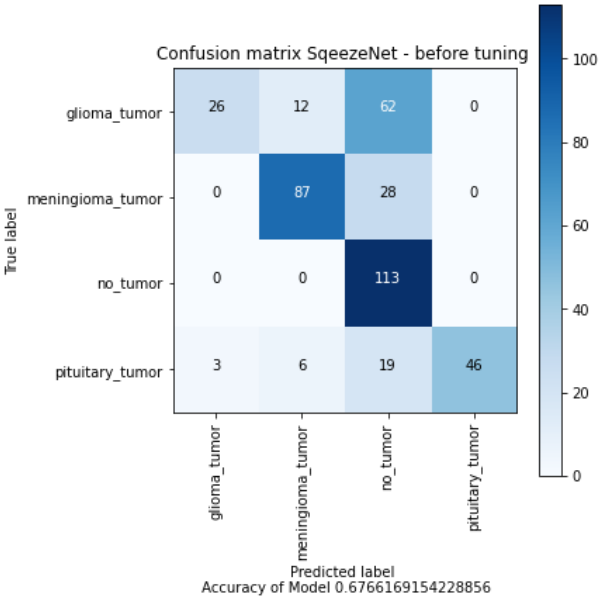
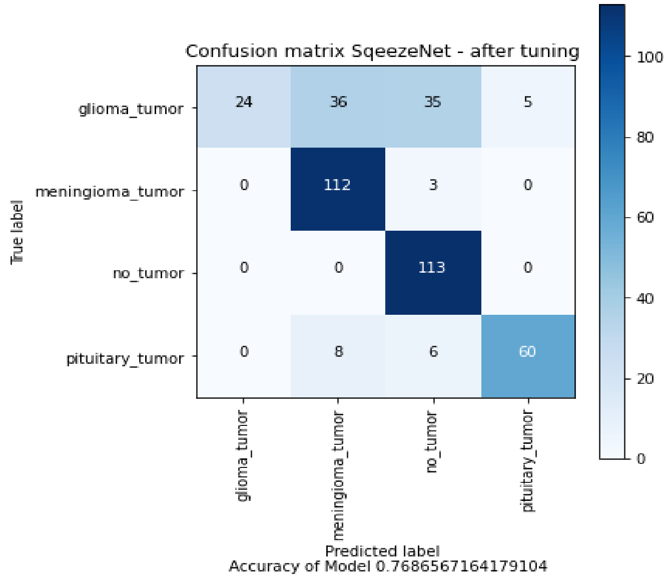

Confusion matrix SqeezeNet - before tuning
True label
glioma_tumor
meningioma_tumor
no_tumor
pituitary_tumor
26
12
62
0
0
87
28
0
0
0
113
0
3
6
19
46
Predicted label
Accuracy of Model 0.6766169154228856
100
80
60
40
20
0


Confusion matrix SqeezeNet - after tuning
True label
glioma_tumor
meningioma_tumor
no_tumor
pituitary_tumor
24
36
35
5
0
112
3
0
0
0
113
0
0
8
6
60
Predicted label
Accuracy of Model 0.7686567164179104
100
80
60
40
20
0