Brain tumor classification using deep CNN

Anamul Hasan Dhusor	170104006
Fuad Hasan	170104010
Maishameem Meherin Muhu	170104017
Nishat Sharmin	170104043

Project Report

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Submitted by

Anamul Hasan Dhusor	**170104006**
Fuad Hasan	**170104010**
Maishameem Meherin Muhu	**170104017**
Nishat Sharmin	**170104043**

Submitted To

Sanzana Karim Lora, Lecturer

Department of Computer Science and Engineering

Ahsanullah University of Science and Technology

Department of Computer Science and Engineering

Ahsanullah University of Science and Technology

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ABSTRACT

Brain tumor classification is an important problem in computer-aided diagnosis (CAD) for medical applications. This paper focuses on a 3-class classification problem to differentiate among glioma, meningioma and pituitary tumors, which form three prominent types of brain tumor. The proposed classification system adopts the concept of deep transfer learning and uses a pre-trained GoogLeNet to extract features from brain MRI images. Proven classifier models are integrated to classify the extracted features. The experiment follows a patient-level five-fold cross-validation process, on MRI dataset from figshare. The proposed system records a mean classification ac- curacy of 98area under the curve (AUC), precision, recall, F-score and specificity. In addition, the paper addresses a practical aspect by evaluating the system with fewer training samples. The observations of the study imply that transfer learning is a useful technique when the availability of medical images is limited. The paper provides an ana- lytical discussion on misclassifications also.

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0.1 Introduction

Brain tumors are a lethal neurological disease caused by abnormal and uncontrolled growth of cells inside the brain or skull. The mortality rate of patients due to this disease is increasing day by day. An early detection of this fatal disease can activate a timely treatment consequently elevating the survival ratio of the patients. So, brain tumor diagnosis is very important in order to develop an effective plan of treatment. There are more than 120 types of brain and Central Nervous System (CNS) tumors. Neurologists classify manually the brain MR images using the World Health Organization (WHO) classification [1]. The Automation of the classification procedure, in particular brain MR images classification help radiologist in their diagnosis and reduce enormously their interventions. To avoid handcrafted features extraction, deep learning (DL) methods involving deep neural networks to classify images in self-learning without the need of handcrafted features extraction are used by Benjio [2] and Litjens et al. [3] . Among several DL methods, Convolutional Neural Networks (CNN) have also yielded good results in medical image application [4] [5] [6]. In recent years, CNN has achieved good results in medical image applications due to the availability of labeled data, the increased power of the Graphics Processing Unit(GPU), the rise of accuracy to solve complicated applications over time and the appearance of voluminous techniques to learn features. Nowadays, several public brain MR images datasets for classification are accessible for researchers. However, the CNNs training becomes more complicated and can lead to overfitting because of the size of samples in medical datasets. Training the networks with transfer learning is usually much faster and easier than training the networks with randomly initialized weights [7] [8] [9].In this paper, we report the overall classification accuracy of the six pre-trained architectures based on training time and epoch number.

0.2 Related Works

0.2.1 List of some related works

We found some related works, most important tow is given bellow-

1. Transfer Learning Using Convolutional Neural Network Architectures for Brain Tumor Classification from MRI Images [10].

2. Brain tumor classification using deep CNN features via transfer learning [11].

0.2.2 Review

A research work was conducted by Rayene Chelghoumet al. [10] of Frères Mentouri University, LARC, Laboratory of Automatic and Robotic, Constantine, Algeria in 2020, proposing system applied the concept of deep transfer learning using nine pre-trained architectures for brain MRI images classification trained for three epochs to reduce consuming time. This paper presened a fully automatic system for three kind of brain tumor (glioma, meningioma and pituitary) classification using CE-MRI dataset from fig-share. . The dataset was collected from Nanfang Hospital, Guangzhou and General Hospital, Tianjin Medical University, in China during 2005–2010. It contained 3064 abnormal brain CE-MRI from 233 patients with three kinds of brain tumor : meningioma (708 slices), glioma (1426 slices), and pituitary tumor (930 slices). They adopted deep transfer learning for feature extraction from brain MR images using nine deep CNNs architectures: AlexNet, GoogleNet , VGG16, VGG19, Residual Networks (ResNet18, ResNet50, ResNet101), Residual Networks and Inception-v2 (ResNetInception-v2), Squeeze and Excitation Network (SENet). This study increased the classification accuracy, speeded the training time and avoided the overfitting. The proposed system outperformed the state-of-the-art pre-trained method and using the VGG16 achieved 98.71% classification accuracy.

Second work [11] also use same methodology with different fine tuning and dataset. They use image form *imagenet* and *Figshare* dataset.

0.3 Project Objective

0.3.1 Data Collection & Processing

We, collect the dataset from **Kaggle called - *Brain Tumor Classification (MRI)*** . Dataset contains images in two folders **train** and **test**. Every forder contains four classes.

1. **glioma_tumor:** Total images 926
2. **meningioma_tumor:** Total images 937
3. **pituitary_tumor:** Total images 901
4. **no_tumor:** Total images 500

Total train data 2870 and test data 394.

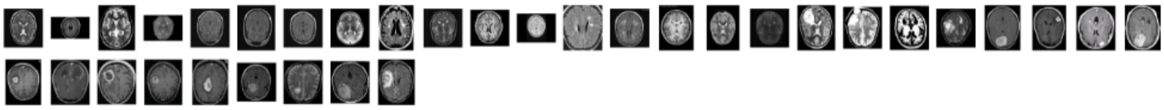

Figure 1: Some images from dataset

0.3.2 Data representation

We only have image data for three types brain tumor and without brain tumor.
Datas are represented like fig 1.

0.3.3 Data Processing

The actual size of the images were [348,278]. For training and test we convert them into [180,180] for *inception_v3*,and [224,224] for *GoogleNet, AlexNet, vgg16, vgg19 and resnet18*.We perform *transforms* for both test and train data. And loaded them into testDataloader and trainDataloader with bathch size 16.

During transforms we do-

1. Resize image
2. Convert image into tensor
3. Normalize the values

0.4 Methodology

We applied six pre-trained deep CNN networks including - AlexNet, inception_v3, GoogleNet, VGG16, VGG19, ResNet18 for brain tumor classification problem using transfer learning.

0.4.1 Pre-trained CNNs Architectures for Image Classification

CNNs architectures have been designed to learn spatial hierarchies of features by building multiple blocks: convolution layers with a set of filters, pooling layers, and fully connected layers (FCLs).

Architectures	precision	recall	f1-score	accuracy
Inception-v3	0.84	0.79	0.79	78
GoogleNet	0.87	0.80	0.80	79
AlexNet	0.84	0.73	0.74	74
VGG19	0.85	0.77	0.77	77
VGG16	0.85	0.77	0.77	77
ResNet18	0.86	0.77	0.77	76

Table 1: Comparison among the results

0.5 Experiments and Results

The proposed classification model is implemented in Kaggle Notebook

Training Parameters: We use Adam optimizer and learning rate 0.0001. A table compering the evaluation of the models given bellow -

0.5.1 Evaluation Metric

As showed at table 1, we use-

- Precision
- Recall
- F1-score
- Accuracy

—- as Evaluation metric.

Loss curves of different architectures are given at fig [2, 3, 4, 5, 6, 7]
Accuracy curves of different architectures are given at fig [8, 9, 10, 11, 12, 13]
Confusion matrix of different architectures are given at fig [14, 15, 16, 17, 18, 19]

If we analyze all these diagram, we will see *GoogleNet* performs better than other five architectures we use.As it gives better result for all used evaluation metric.

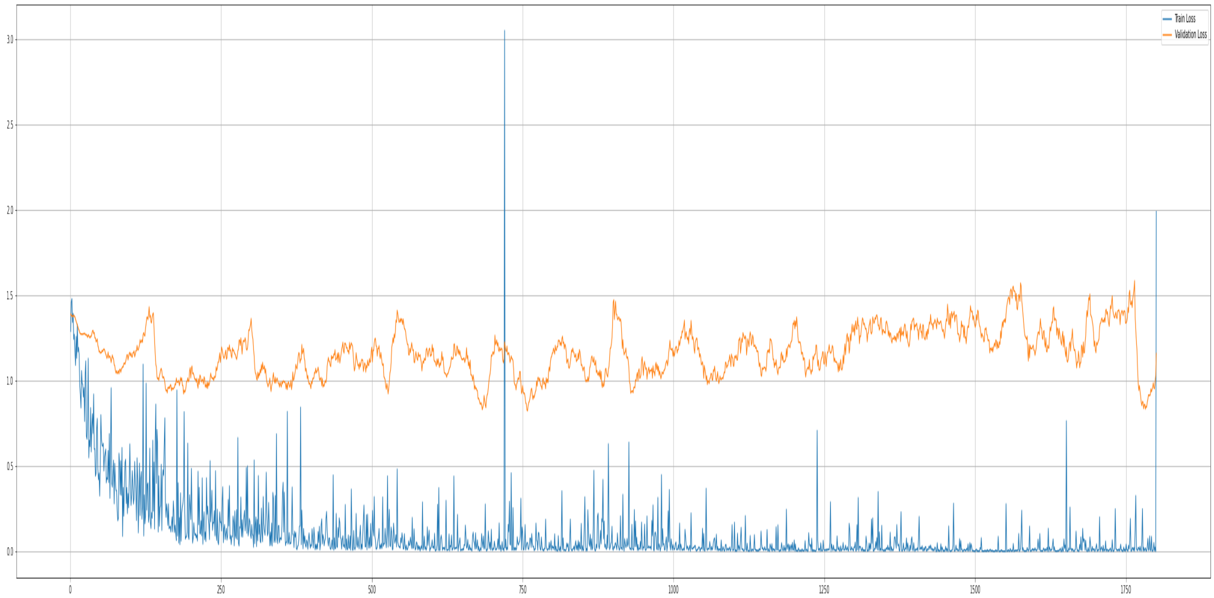

Figure 2: inceptionv3 loss curve

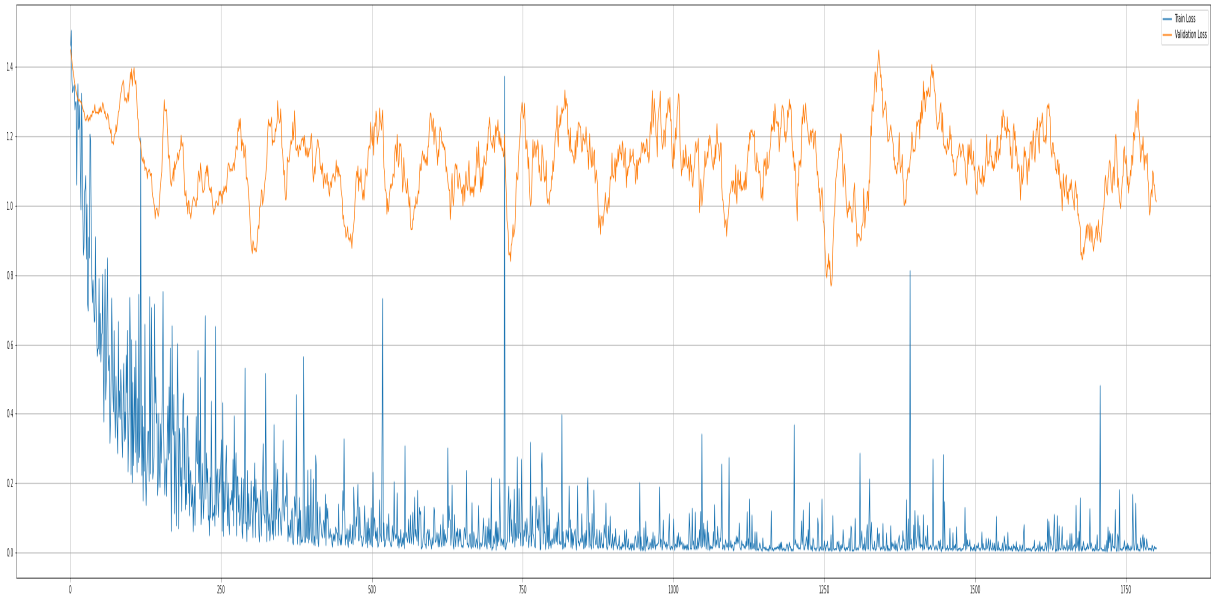

Figure 3: GoogleNet loss curve

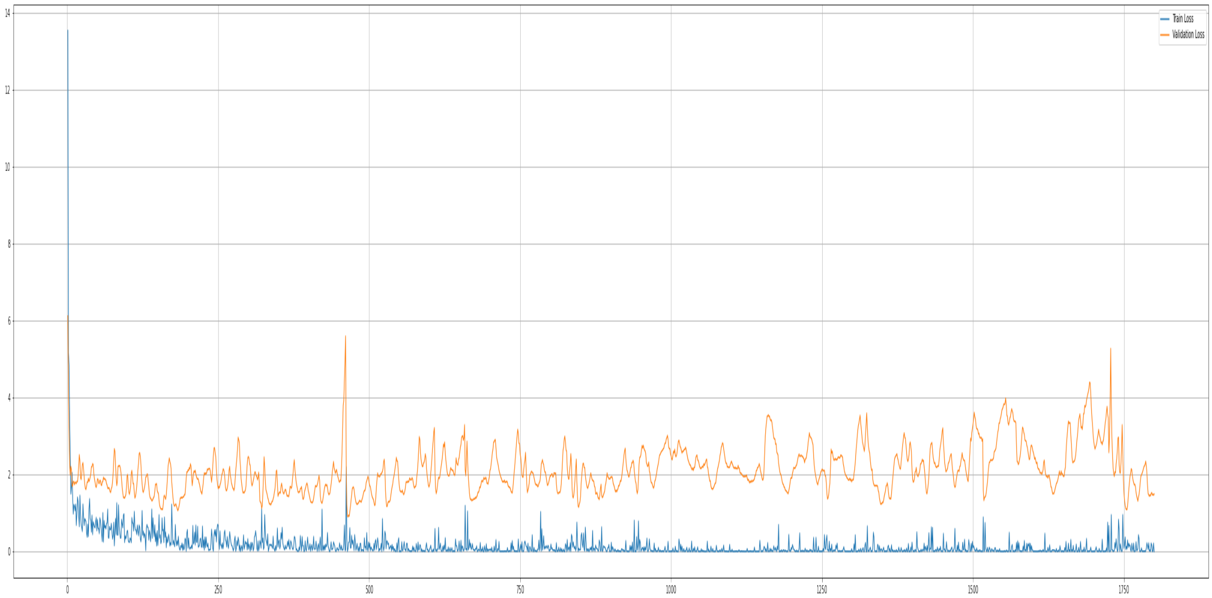

Figure 4: VGG16 loss curve

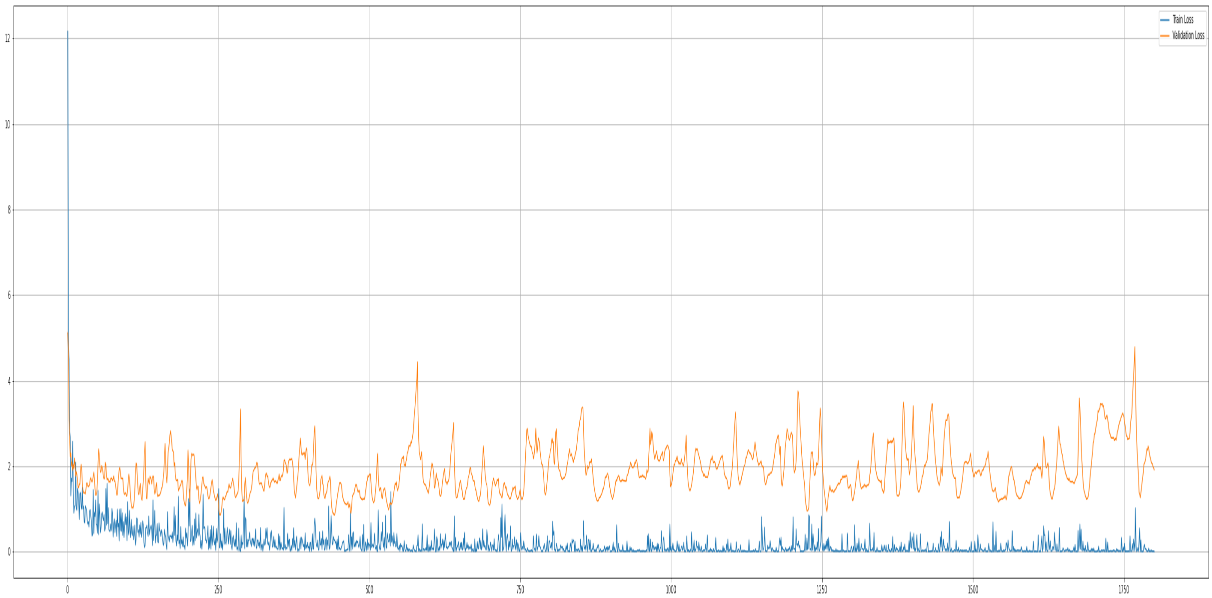

Figure 5: VGG19 loss curve

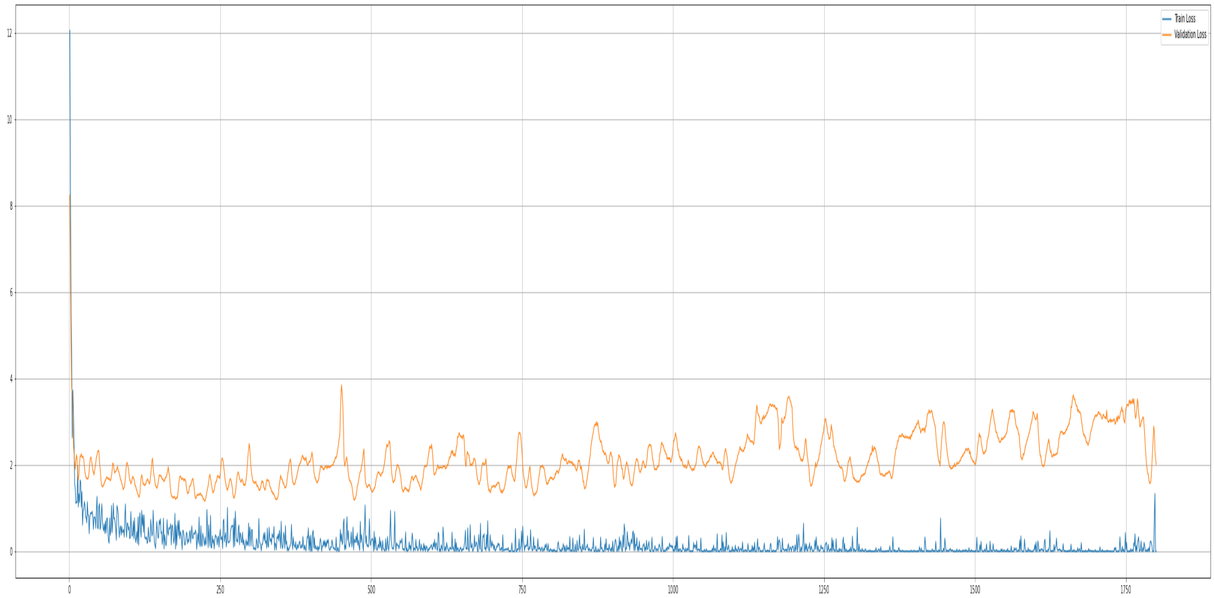

Figure 6: AlexNet loss curve

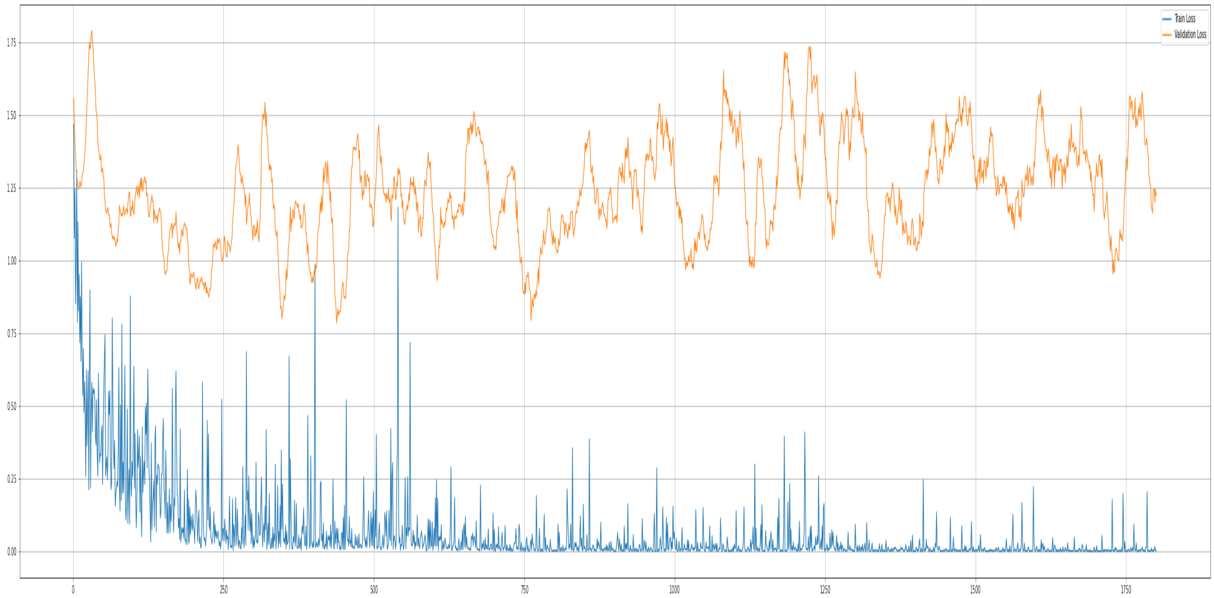

Figure 7: ResNet18 loss curve

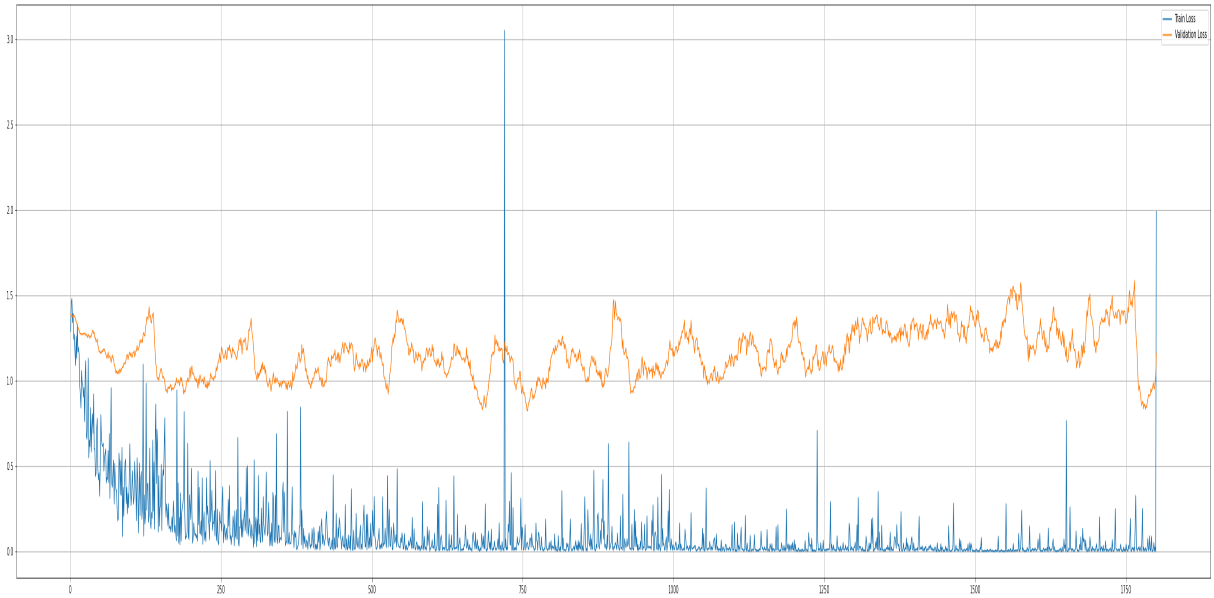

Figure 8: inceptionv3 loss curve

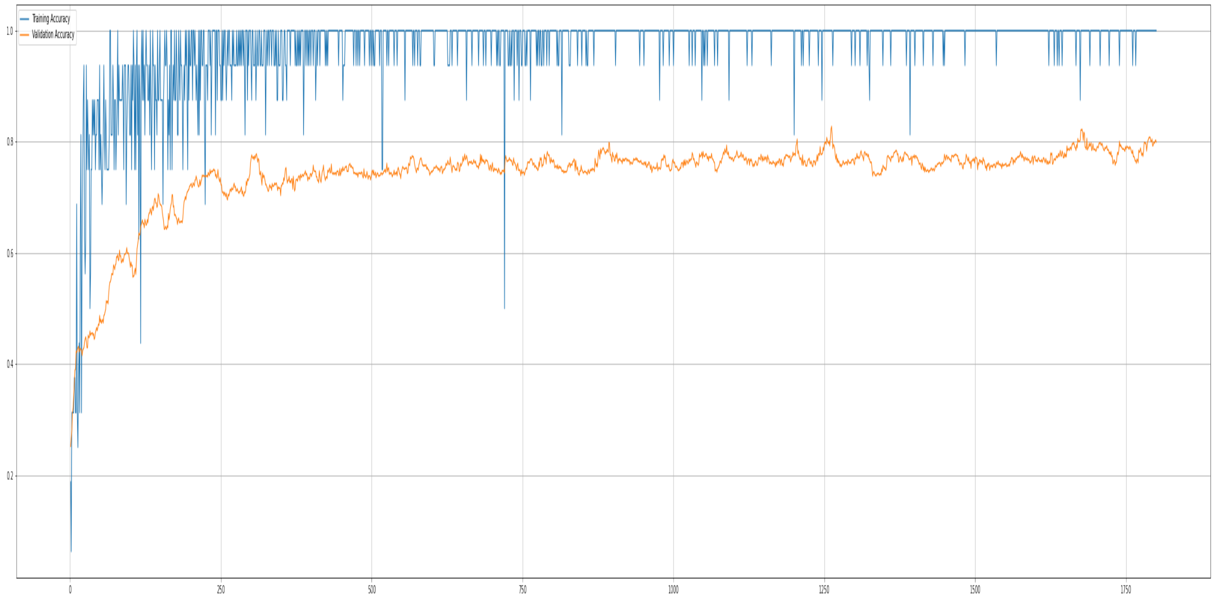

Figure 9: GoogleNet accuracy curve

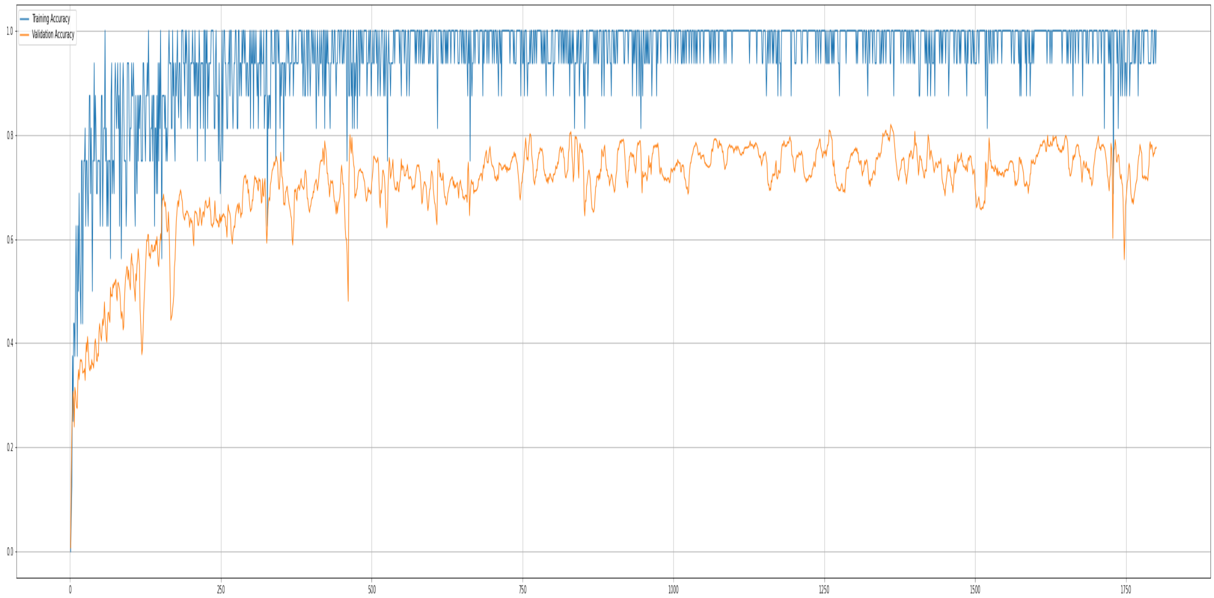

Figure 10: VGG16 accuracy curve

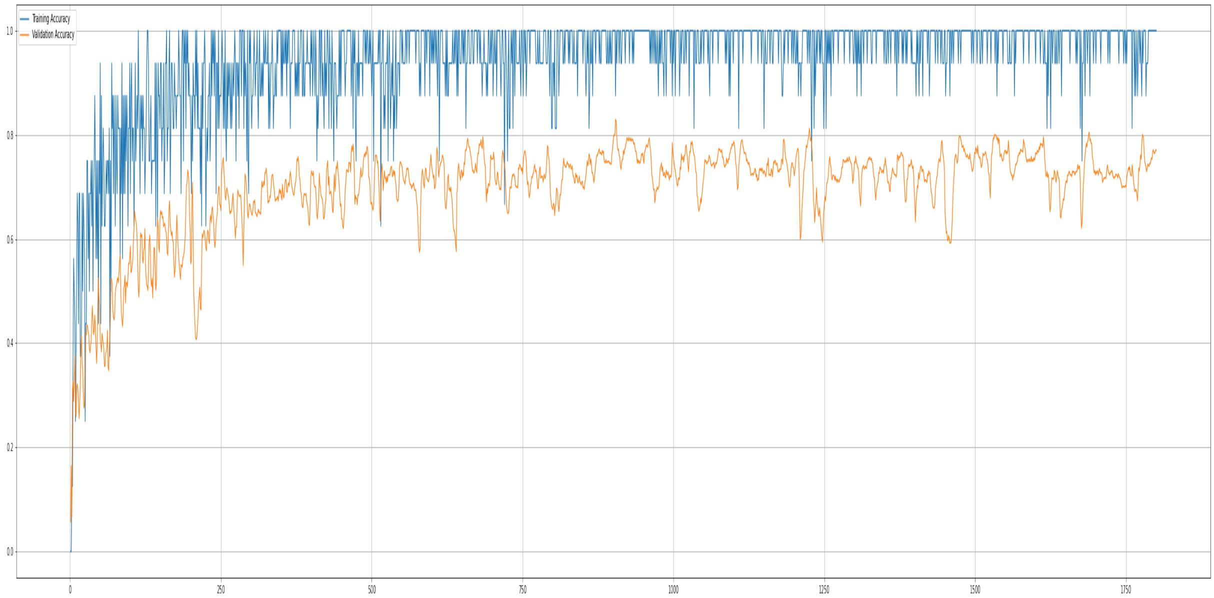

Figure 11: VGG19 accuracy curve

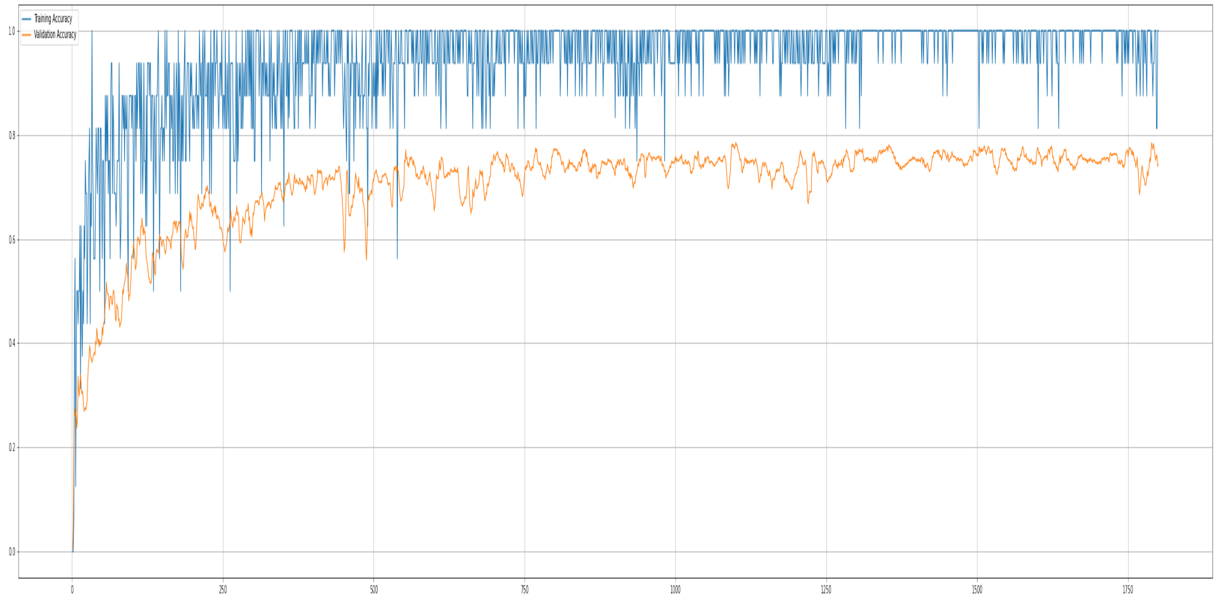

Figure 12: AlexNet accuracy curve

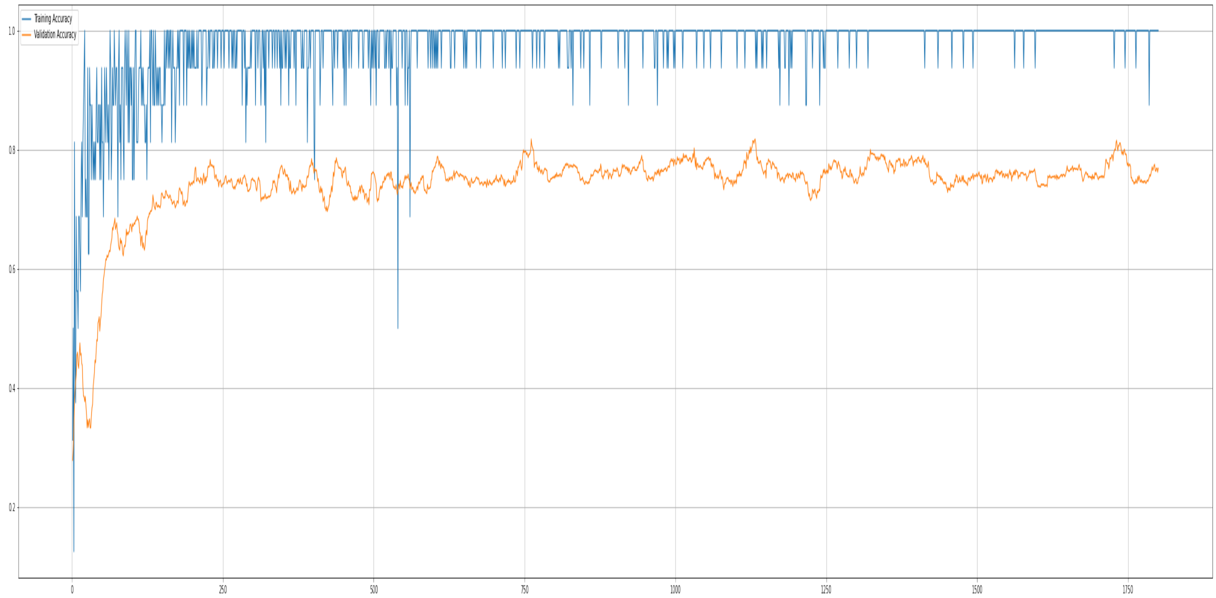

Figure 13: ResNet18 accuracy curve

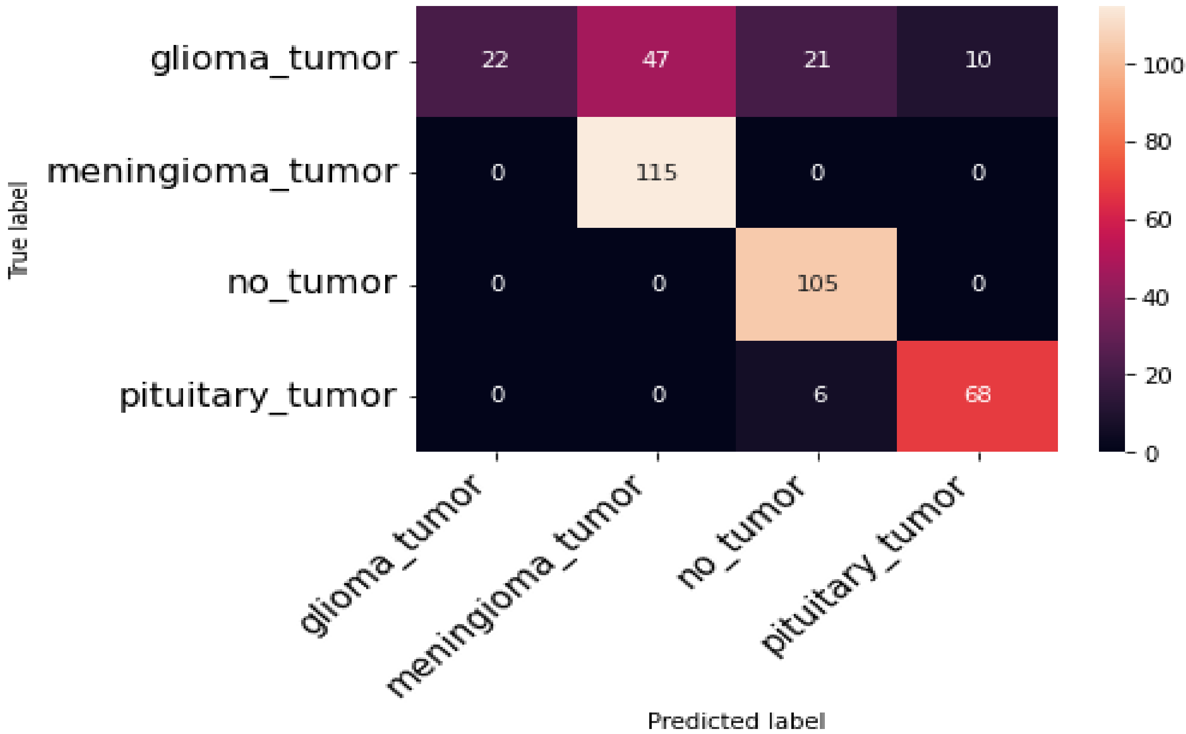

Figure 14: inceptionv3 confusion matrix

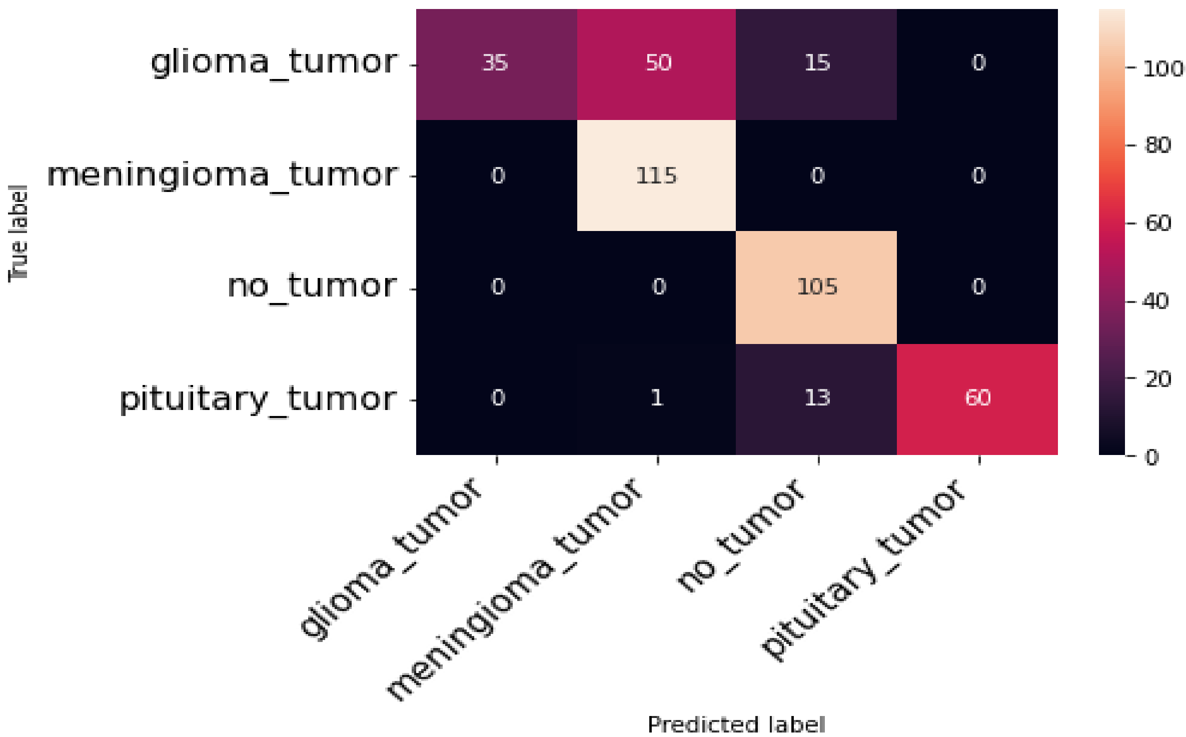

Figure 15: GoogleNet confusion matrix

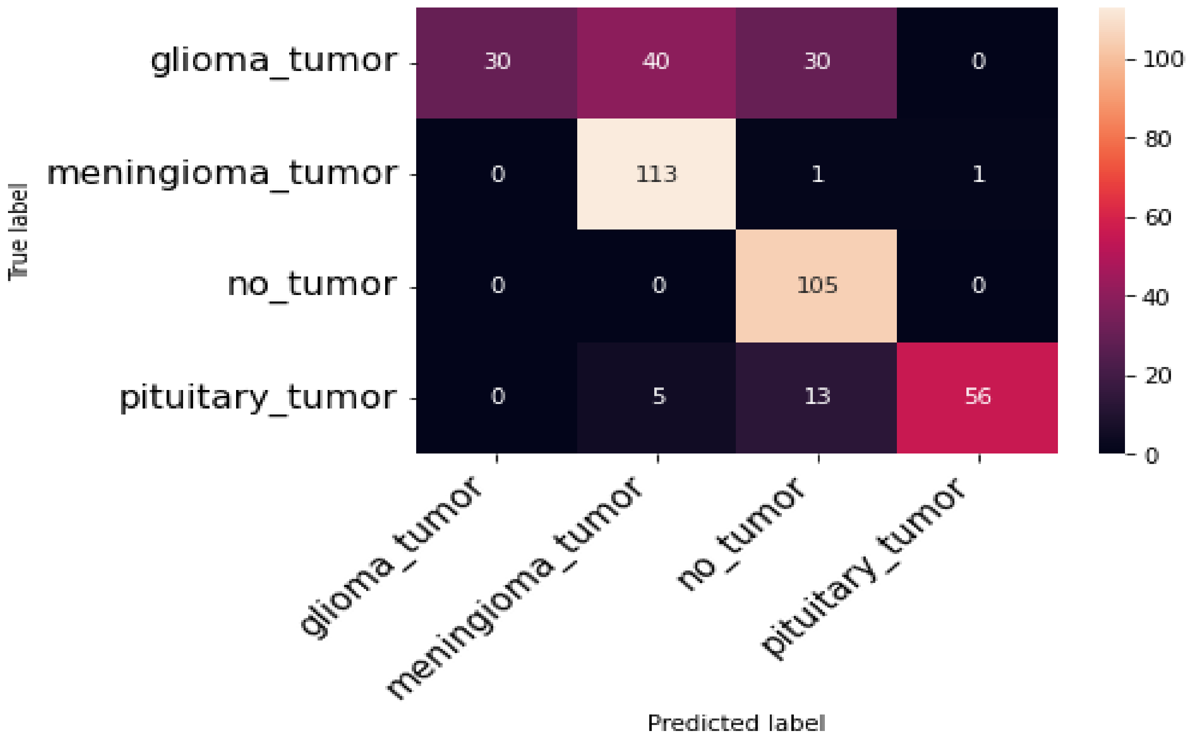

Figure 16: VGG16 confusion matrix

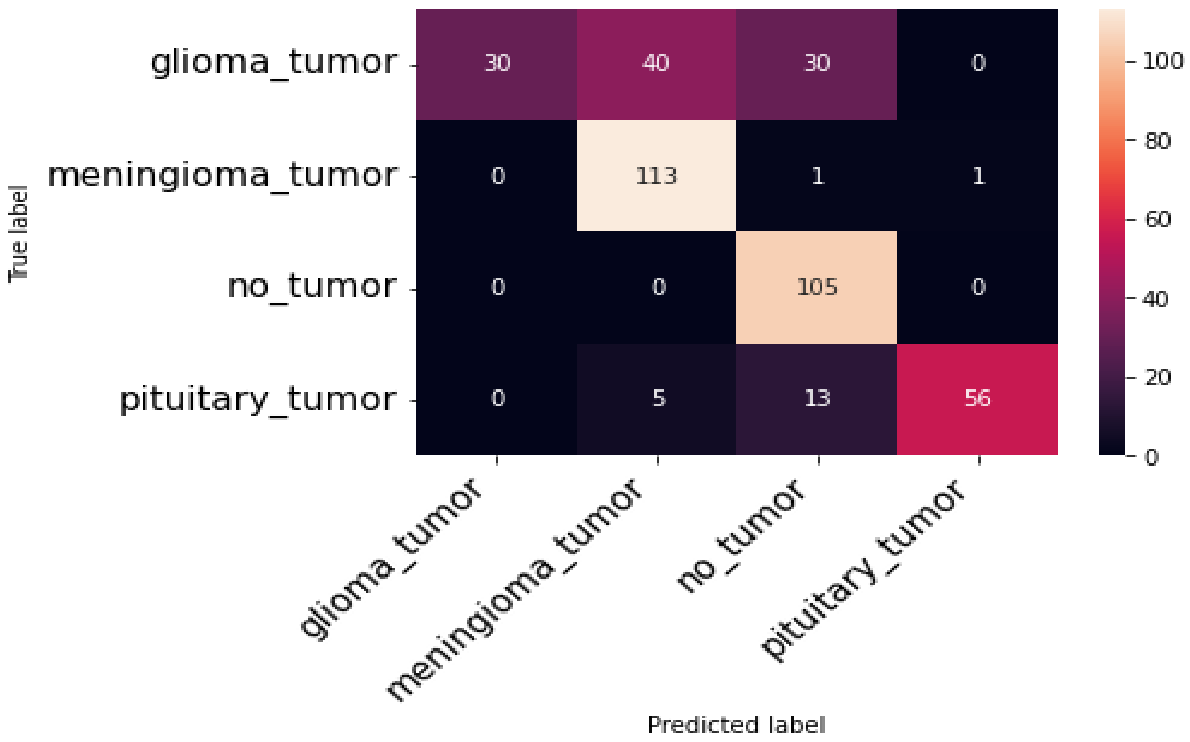

Figure 17: VGG19 confusion matrix

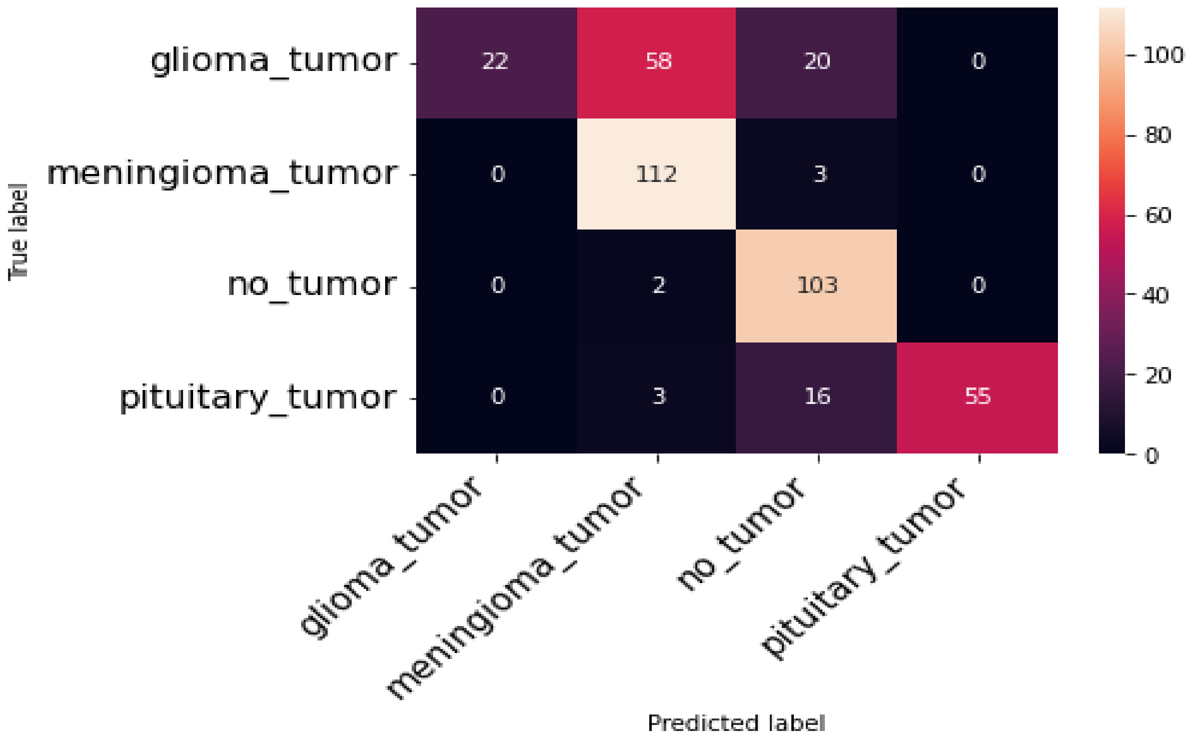

Figure 18: AlexNet confusion matrix

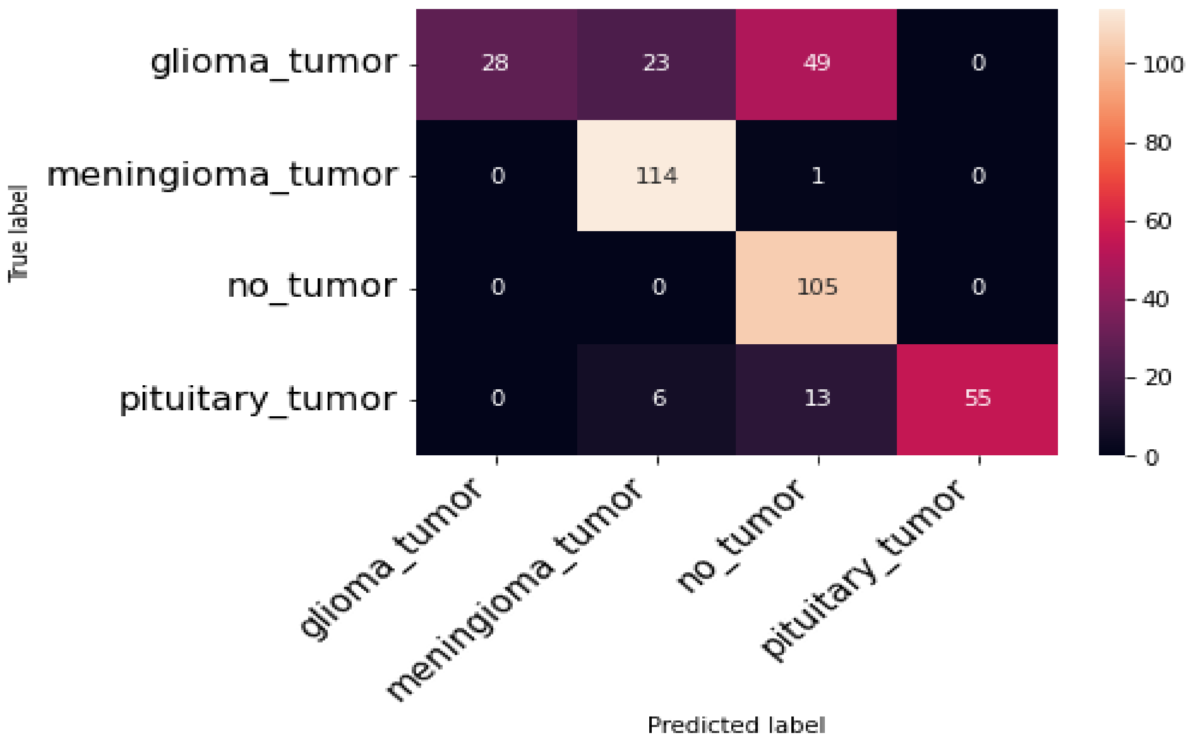

Figure 19: ResNet18 confusion matrix

0.6 Conclusion and Future Directions

0.6.1 Conclusion

Due to the high image resolution it provides, MRI helps detect abnormalities in the brain with greater ease . Traditionally, MR images are interpreted by radiologists and tumors are diagnosed. However, with the advances in medical imaging techniques, it has become difficult to interpret manually large amounts of data produced in reasonable periods. As deep learning can effectively identify complex relationships, it has begun to attract great attention in the field of medical image analysis. This paper presents a fully automatic system for three kind of brain tumor classification using dataset from Brain Tumor Classification (MRI). The proposed system applied the concept of deep transfer learning using nine pre-trained architectures for brain MRI images classification trained.

0.6.2 Future Work

In the future work, we will apply our system to classify medical images from different modalities such as X-rays, Positron Emission Tomography (PET) and Computed Tomography (CT) for other body organ.

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