Applications of various convolutional neural networks for classification of brain tumor images

Volegova Darya,
Bauman Moscow State Technical University
Russia, Moscow
dariavolegova24@gmail.com

Abstract

With the development of artificial intelligence, it becomes possible to use it to classify medical images. Large data streams obtained as a result of patient examinations can be analyzed with greater speed and sufficient accuracy. This article presents the results of the analysis of MRI images of the brain for the presence of tumors by using convolutional neural networks.

***K*eywords** Brain tumors · Neural networks · VGG · Resnet50 · Googlenet

1 Introduction

A brain tumor is one of the most common and deadly types of cancer. In recent decades, much attention has been paid to the diagnosis of this disease in order to reduce negative formative factors and provide timely diagnostics. Thus, in the period from 1975 to 1977 and from 2009 to 2015, the survival rate with a malignant brain tumor increased from 23 percent to 36 percent [1].

Benign tumors also affect the internal structures of the brain, as their growth causes compression of surrounding tissues. Some of the known tumors are glioma and meningioma. Glioma is a growth of cells that starts in the brain or spinal cord [2]. The cells in a glioma look similar to healthy brain cells called glial cell. Glial cell surround nerve cells and help them function. As a glioma grows it forms a mass of cells called a tumor. In turn, Meningioma is a primary tumor of the central nervous system (CNS) [3]. This means that it begins in the brain or spinal cord. In general, meningiomas are the most common type of primary brain tumor.

The use of convolutional neural networks is widespread in various fields of medicine [4]. Convolutional neural networks are used in the diagnosis of brain lesions caused by Alzheimer's disease [5] or brain tumors [6]. The main tasks in this case are image classification, segmentation, localization and detection. Thus, the use of neural networks for the analysis of MRI images of brain tumors remains an urgent task. The analysis of MRI images using neural networks is possible using various architectures, namely AlexNet, VGG, GoogLeNet, ResNet, DenseNet, NASNet, U-net and others [7].

Thus, the need to develop methods for studying and analyzing MRI images is solved using deep machine learning models, namely convolutional neural networks and the use of Transfer Learning methods.

2 Features of the selected convolutional neural networks

2.1 ResNet50

Features of the network ResNet50 due to which it was chosen to complete the task:

- Networks with large number (even thousands) of layers can be trained easily without increasing the training error percentage.
- ResNets help in tackling the vanishing gradient problem using identity mapping.
- ResNets accelerate the speed of training of the deep networks.

- Instead of widen the network, increasing depth of the network results in less extra parameters.
- Reducing the effect of Vanishing Gradient Problem.
- Obtaining higher accuracy in network performance especially in Image Classification.
- Use of the Adam optimization algorithm for fast and efficient network training.
- The ResNet architecture does not need to fire all neurons in every epoch. This greatly reduces the training time and improves accuracy. Once a feature is learnt, it does not try to learn it again but rather focuses on learning newer features. A very smart approach that greatly improved model training performance.

The ResNet50 network can be chosen for image classification because of its architecture that overcame the “vanishing gradient” problem, making it possible to construct networks with up to thousands of convolutional layers, which outperform shallower networks [8].

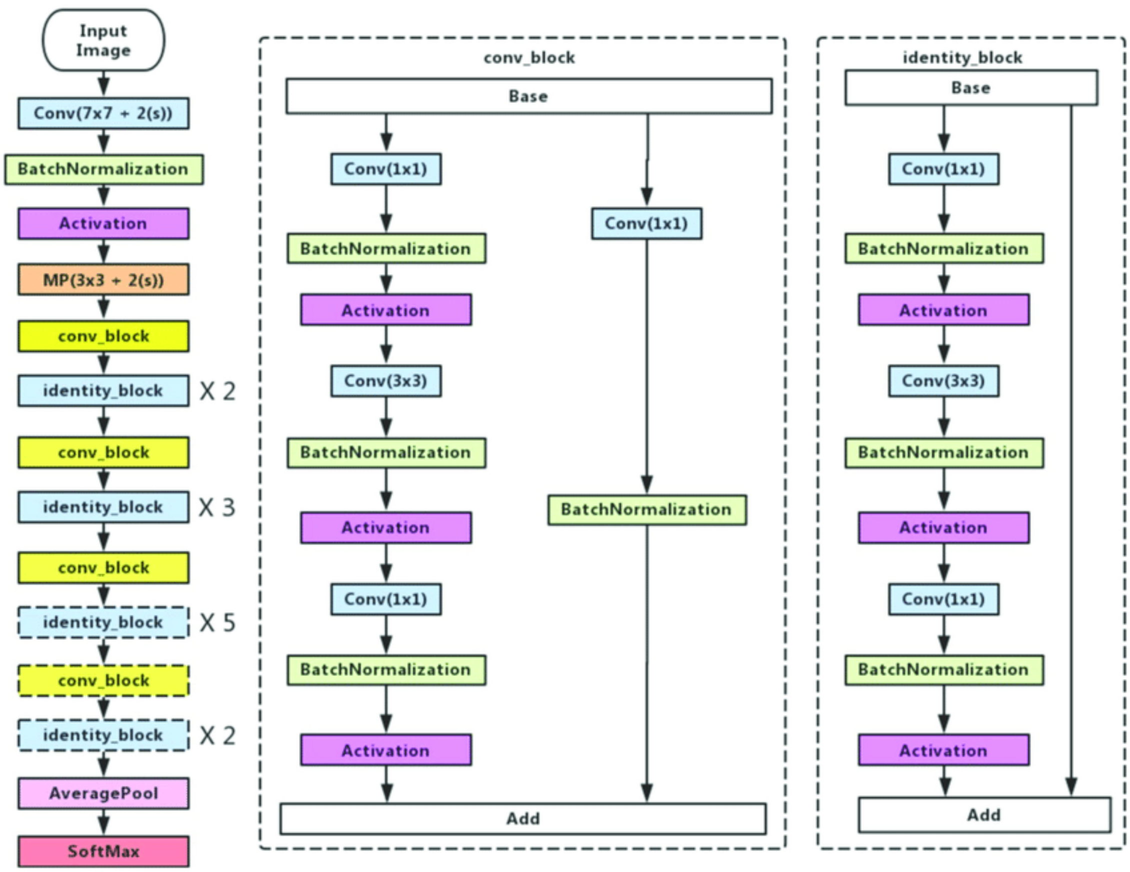

Figure 1: Resnet50 network architecture.

2.2 GoogLeNet

Features of the network GoogLeNet due to which it was chosen to complete the task:

- GoogleNet trains faster than VGG.
- Size of a pre-trained GoogleNet is comparatively smaller than VGG. A VGG model can have > 500 MBs, whereas GoogleNet has a size of only 96 MB.
- GoogleNet achieves higher efficiency by compressing the input image and simultaneously retaining the important features/information.

GoogleNet network can be selected because of the high speed of operation.

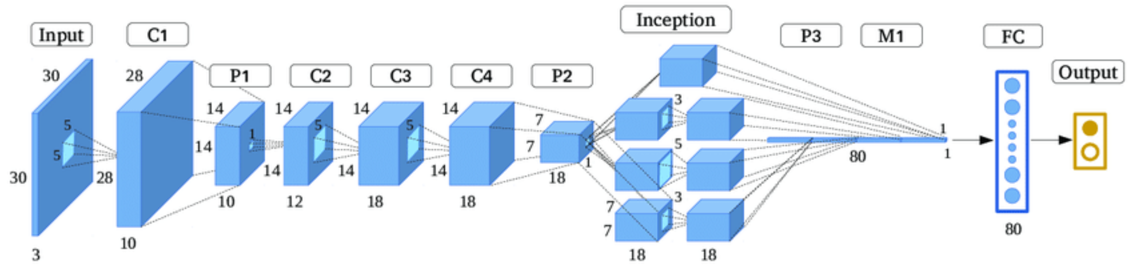

Figure 2: GoogleNet network architecture.

2.3 VGG

Features of the network VGG due to which it was chosen to complete the task:

- VGG uses very small receptive fields instead of massive fields
- VGG16 will work better than ResNets in cases where only lower level features are crucial for classification such as small lines, curves etc.

Even though ResNet is much deeper than VGG16 and VGG19, the model size is actually substantially smaller due to the usage of global average pooling rather than fully-connected layers — this reduces the model size down to 102MB for ResNet50.

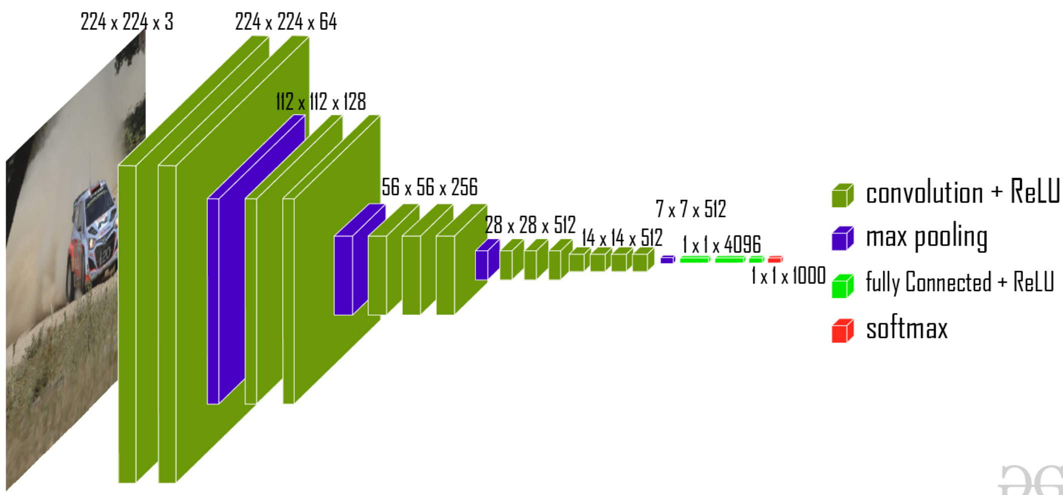

Figure 3: VGG16 network architecture.

3 Related Work

4 Methods

To conduct the study, a publicly available (from open sources) MRI images of brain dataset was taken from the Kaggle website. This dataset contains an image section of gloioms, menengioms and images with no tumors.

4.1 Classify photos of tumors

To classify photos of tumors using the network, follow these steps:

1. Create a dataset of MRI images for training, dividing the general population into training, validation and test data.
2. Convert all images to a single view.
3. Load the model and its pre-trained weights.
4. Change the structure of the neural network by replacing the fully connected layer.
5. Train the model using the training set and validate it using the validation set.
6. Fine-tune the model by adjusting the hyperparameters and optimizing the loss function.
7. Test the model on the testing set and evaluate its accuracy and performance.

4.2 Research results obtained using ResNet50

ResNet was developed in 2015 and it is worth noting that it has sufficient accuracy. For example, when training on the ImageNet dataset, it is possible to achieve accuracy of up to 98 percent.

When using the ResNet network, training was conducted on a training dataset with intermediate validation on a validation dataset for 7 epochs. Thus, the obtained accuracy in the training sample reached 95 percent and when tested on test data - 94.26 percent.

4.3 Research results obtained using GoogLeNet

GoogLeNet was developed in 2014. Currently, this is the main architecture in most common ML libraries, such as TensorFlow, Keras, PyTorch, etc. And with transfer learning, you can use the imagenet-trained GoogLeNet network without implementing or training the network yourself.

When using the GoogLe Net network, training was conducted on a training dataset with intermediate validation on the validation dataset for 7 epochs. Thus, the obtained accuracy in the training sample reached 79,62 percent, and when tested on test data - 80.81 percent.

4.4 Research results obtained using VGG

The VG 16 model can achieve a test accuracy of 92.7 percent in Imagine, a dataset containing more than 14 million training images across 1000 object classes. It is one of the top models from the ILSVRC-2014 competition. VG 16 improve on Alex Net and replaces the large filters with sequences of smaller 3=3 filters.

When using the GoogLe Net network, training was conducted on a training dataset with intermediate validation on the validation dataset for 4 epochs. Thus, the obtained accuracy in the training sample reached 95,30 percent, and when tested on test data - 90.31 percent.

5 Graphs

5.1 Graphs of accuracy versus number of epochs

Below are the graphs for each Convolutional Neural Network. The blue color indicates the graphs related to the training sample data, orange - to the validation sample data.

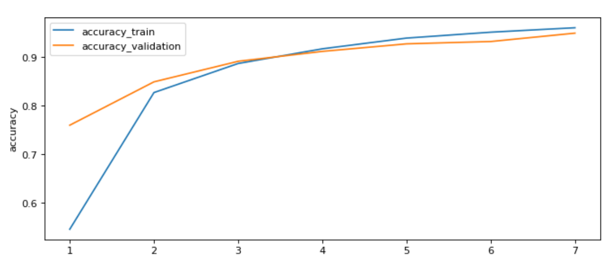

Figure 4: Resnet50 accuracy.

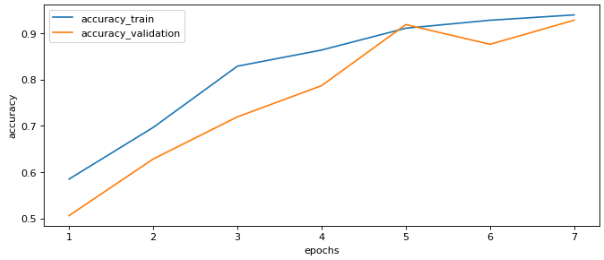

Figure 5: GoogLeNet accuracy.

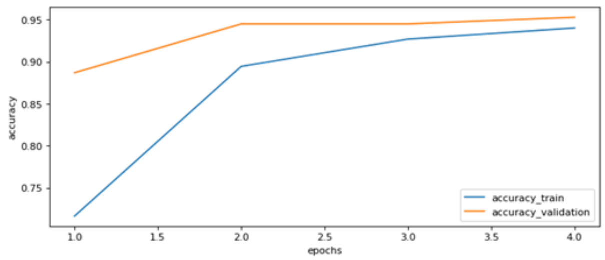

Figure 6: VGG16 accuracy.

5.2 Graphs of loss versus number of epochs

Below are the dependences of the losses of the training set and validation set on the number of epochs for each Convolutional Neural Network

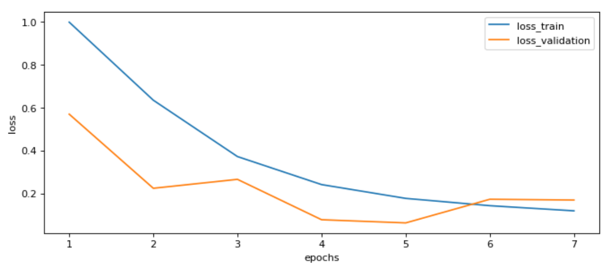

Figure 7: Resnet50 losses.

6 Comparison of all obtained results

The solution of the project described in this article is presented on the open source platform GitHub in the public repository at the link:

`https://github.com/DariaVol24/Transfer-Learning`

References

[1] Brain And Other Central Nervous System Tumor Statistics. *A Cancer Journal for Clinicians*, (71/5), 2021.

[2] Oronsky B. et al. A review of newly diagnosed glioblastoma. *Frontiers in Oncology*, 10:574012, 2021.

[3] Adamson D. C. Ogasawara C., Philbrick B. D. Meningioma: a review of epidemiology, pathology, diagnosis, treatment, and future directions. *Biomedicines*, 9:319, 2021.

[4] Convolutional Neural Networks In Medical image Understanding: A Survey. *Evolutionary Intelligence*, 15:1–22, 2022.

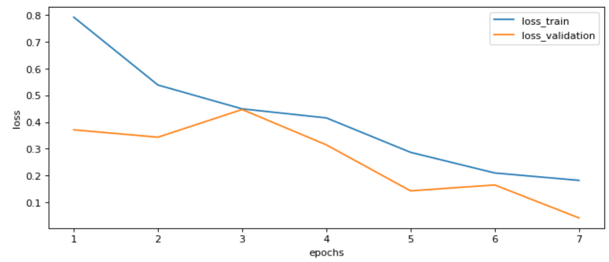

Figure 8: GoogLeNet losses.

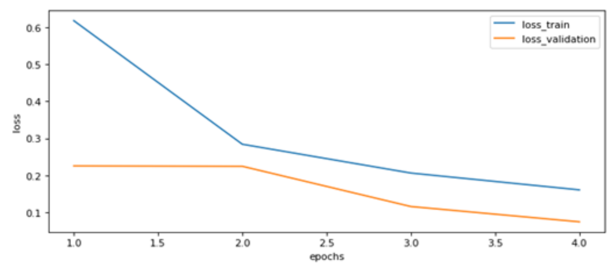

Figure 9: VGG16 losses.

[5] Qinquan Gao Di Guo Xiaofeng Du Yonggui Yang Gang Guo Min Xiao Min Du Xiaobo Qu8 Weiming Lin, Tong Tong. Convolutional neural networks-based mri image analysis for the alzheimer's disease prediction from mild cognitive impairment. *Frontiers in neuroscience*, 12:777, 2018.

[6] Zhang Z. Gao Z., Wang G. Neural network algorithm mri images for analysis of influencing factors for patellar dislocation in exercise. *Scientific Programming*, pages 1–8, 2021.

[7] Lundervold A. S. Lundervold a. an overview of deep learning in medical imaging focusing on mri. *Zeitschrift für Medizinische Physik*, 29:102–127, 2019.

[8] Ji Q. et al. Optimized deep convolutional neural networks for identification of macular diseases from optical coherence tomography images. *Algorithms*, 12:51, 2019.