Leukemia Classification

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Abstract

ResNet50, GoogLeNet and VGG16 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 cells images for identifying immature leukemic blasts from normal cells by using convolutional neural networks.

1 Introduction

Acute lymphoblastic leukemia (ALL) accounts for approximately 25 percent of childhood cancers. In general, the task of identifying immature leukemic blasts from normal cells under the microscope is challenging because morphologically, the images of the two cells appear similar. [1] Therefore, the use of neural networks should simplify the task of classifying cancer cells. In this paper, neural network models are ResNet50, GoogleNet and VGG16.

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 [2].

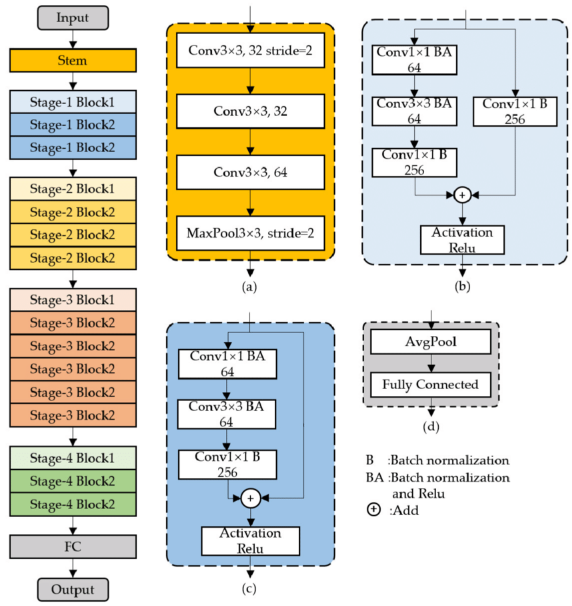

Figure 1: ResNet50 architecture

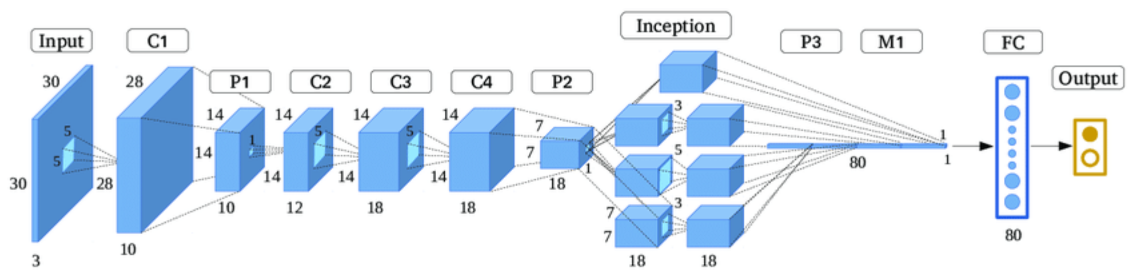

Figure 2: GoogleNet architecture

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. [3]

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. [4]

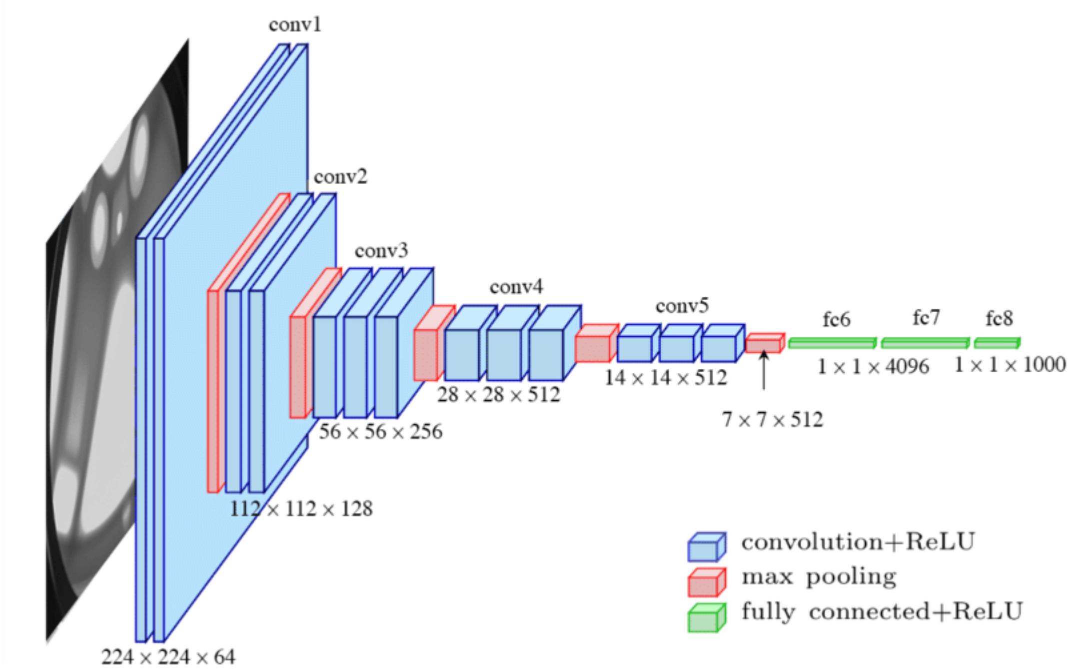

Figure 3: VGG16 achitecture

3 Methods

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

3.1 Research results obtained using ResNet

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 5 epochs. Thus, the obtained accuracy on validation dataset - 85 percent.

3.2 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 5 epochs. Thus, the obtained accuracy on validation dataset - 74 percent.

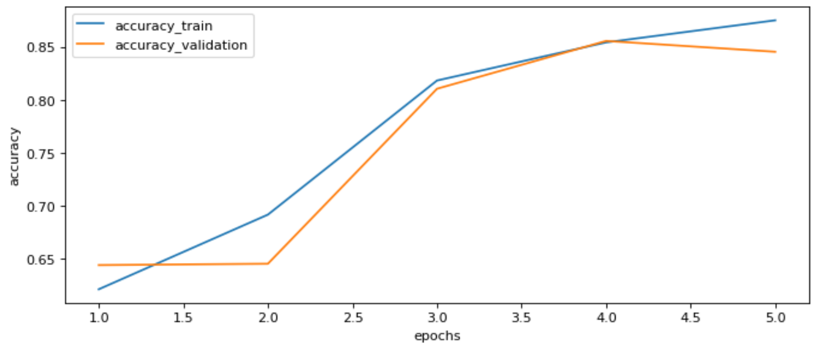

Figure 4: ResNet accuracy

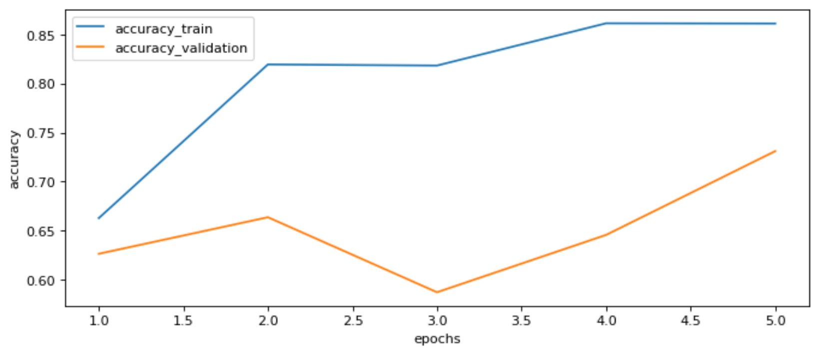

Figure 5: GoogleNet accuracy

3.3 Research results obtained using VGG16

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 on validation dataset - 74 percent.

4 Graphs

4.1 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.

4.2 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

5 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/mamaevki/Leukemia_Classification.git

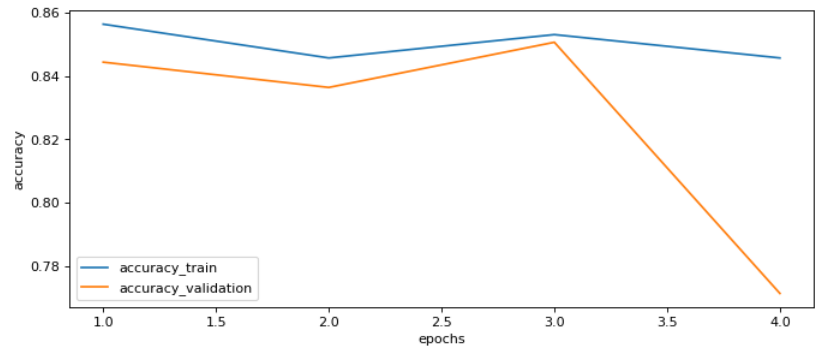

Figure 6: VGG16 accuracy

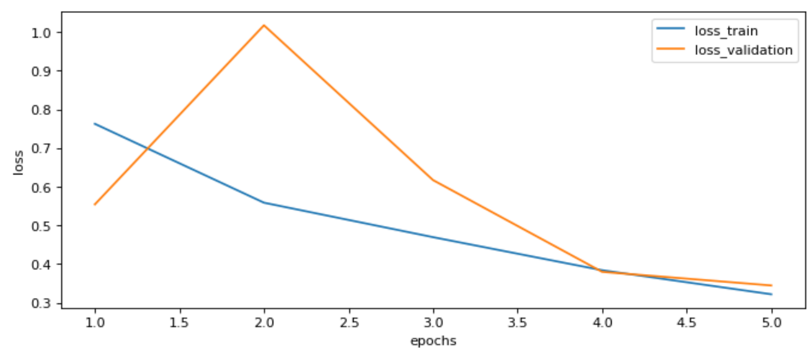

Figure 7: ResNet loss

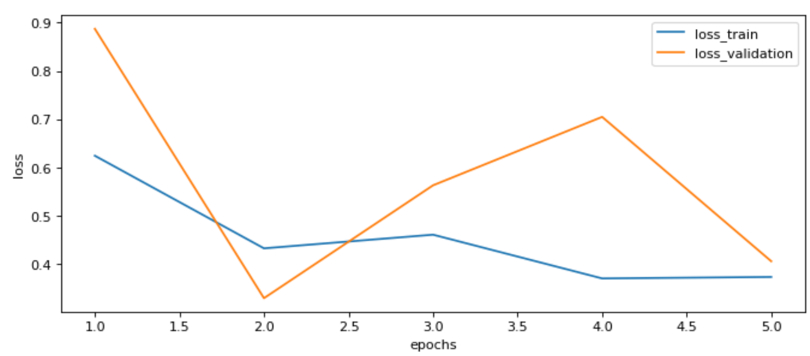

Figure 8: GoogleNet loss

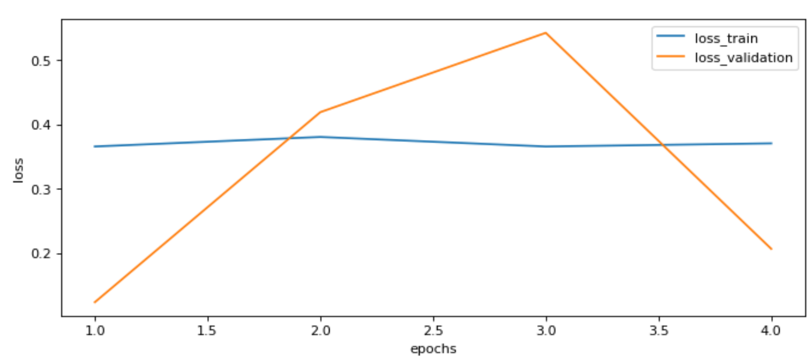

Figure 9: VGG16 loss

6 References

1. Anubha Gupta, Rahul Duggal, Shiv Gehlot, Ritu Gupta, Anvit Mangal, Lalit Kumar, Nisarg Thakkar, and Devprakash Satpathy, "GCTI-SN: Geometry-Inspired Chemical and Tissue Invariant Stain Normalization of Microscopic Medical Images," Medical Image Analysis, vol. 65, Oct 2020

2. Max Ferguson, Ronay ak, Yung-Tsun Tina Lee, Kincho H. Law: Automatic localization of casting defects with convolutional neural networks, Dec 2017

3. Zhiling Guo, Qi Chen Guangming, Guangming Wu, Xiaowei Shao: Village Building Identification Based on Ensemble Convolutional Neural Networks, Oct 2017

4. Shuai Wang, Xiaojun Xia, Lanqing Ye, Binbin Yang: Automatic Detection and Classification of Steel Surface Defect Using Deep Convolutional Neural Networks, Feb 2021