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# Deep Learning Transfer Methods for Biomedical Classification of Images

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**ABSTRACT:** Research using computers has been carried out on the effectiveness of applying deep learning transfer methods to solve the problem of identifying human brain tumors using MRI imaging. Various deep learning and fine-tuning methodologies of models have been proposed and implemented. The deep convolution networks MobileNetV2, VGG-16, Xception and ResNet-50, trained on the ImageNet image set, were used as basic models. A deep convolutional neural network 2D-CNN has also been developed and trained. A computer study of the performance indicators revealed that the fine-tuning method was effective On an enlarged data set, the Xception model outperformed other deep learning models in terms of accuracy: the clarity with which brain tumors are classified using MRI images was 94%, precision 97.7%, recall 94.01%, f1 score 96%, AUC 96.90%.

**KEYWORDS:** brain tumor, MRI images, Statistical modeling, convolution neural networks, transfer of deep learning.

## INTRODUCTION

Deep convolution neural networks (CNN) have shown promise in recent year's impressive success in a wide variety of digital medicine tasks[1, 2]. CNNs are employed in anatomical physiology in the fields of radiography and medical imaging for structures of anatomy and organ segmentation, tissue lesions, etc. Magnetic resonance imaging (MRI) has become one of the generally accepted medical methods for diagnosing tumors of various origins. The radiologist usually performs the diagnosis of MRI images manually, but such a procedure can be time-consuming and its results depend on the experience of the doctor. In addition, it is impossible to view a large number of MRI images in a short time and not make mistakes. Therefore, the development of automated systems for processing and analyzing MRI images becomes an urgent approach[3]. In practice, learning CNN from scratch can be quite a difficult task, since, as a rule, it is impossible to have a data set with a sufficient number of samples. At the same time, the information obtained as a result of training a neural network on one or more data sets can be used to solve another problem on other data[4]. As an example, if a neural network learns to detect items in pictures, that are like lesions on the skin, this information may be utilized to identify other objects in radiological diagnostics [5].This approach in deep learning is called transfer learning, or Transfer Learning (TL). The present work is devoted to studies of the effectiveness of TL methods in the detection of brain tumors based on the analysis of MRI images using pre-trained deep convolutional neural networks[6]. To conduct computer experiments and compare performance, neural networks with pre-trained weights were used on the ImageNet database (a data set of 13 million high-resolution labeled images belonging to more than 20,000 categories) [7, 8]. The aim of the work was to develop effective learning strategies and fine-tuning of deep neural networks for the recognition of human brain tumors with high accuracy.

## TRANSFER LEARNING METHODS IN IMAGE RECOGNITION

The best known method of transfer learning is that as the base classifier model one of the pre-trained deep convolutional networks is used, in which all convolutional and pooling layers are frozen (disabled), and the output layers responsible for the settings of the classifier of the data on which it was trained are also removed[9]. The freezing operation here refers to the procedure for fixing the values of the weights of convolutional layers in such a way that they will not be updated during model training. Next, an alignment layer (Flatten), several fully Connected Layers (Fully Connected Layers) with thinning and dense layers (Dense Layers) are connected to the base model in order to avoid retraining. Finally, the last fully connected layer with the "softmax" activation function is attached to the model, indicating the required number of classes, and its compilation is performed. The model constructed in this way can already be trained to solve a specific task[10].

Another approach is related to the need for fine tuning of the model (Fine Tuning Model) [11]. While in the above method, the classifier is simply connected to Fine-tuning a pre-trained neural network results in changes so that it is more adaptable and efficient in solving the task, for example by sequentially connecting frozen convolutional layers of the model and optimizing its parameters.

The paper proposes the following algorithm for fine-tuning the parameters of a neural network:

(1) Load the base model with its weights trained on ImageNet;
(2) replace the previous completely linked layer by a new completely linked layer;
(3) freeze the model layers to the last convolutional block of the base model;
(4) Retrain the last convolution block and the fully connected layers with the selection of the learning rate.

The learning strategy of the deep neural network model constructed in this way significantly depends on a number of factors. If the data set used is large in size and similar to ImageNet, then a pre-trained model will be a good solution for the task. When implementing a classifier model based on it, it is necessary to use the required number of dense layers as additional layers. If the new data set is small, but similar to ImageNet, then the classical method of transferring training should be applied. In this case, also network setup will be considered as classifier training[12]. If the data set is small and very different from the ImageNet image set, then the best strategy for configuring the model is to train it with sequential unfreezing of the convolutional layers of the pre-trained model, starting from the last one, until an acceptable classification accuracy is achieved on the used set of images. If the data set is large enough, but significantly different from ImageNet, then the best strategy would be to train a deep convolutional network model from scratch, but it should still be initialized with weights from ImageNet [13].

There are a number of pre-trained models that can be used to classify MRI images using the learning transfer strategies proposed above. Their choice was connected both with their popularity among researchers and with the desire to apply the most modern and effective of them.

## DESCRIPTION OF THE DATA SETS UNDER STUDY AND THEIR PRELIMINARY PROCESSING

As a database for comparative analysis of the performance of the studied deep learning models in the work, sets of MRI brain images from the work were used [14]. There are 251 images in the set, 153 of which belong to the "Tumor" class, and 96 images belong to the "No Tumor" class. Since the pre-trained models used require the images to have dimensions of 224x224x3 pixels, the images from the dataset were reduced to this format.

The volume of the initial data set was very small, which could lead to large errors in the model forecasts [15, 16]. To solve this problem, the data augmentation method was used . Using this method, you can increase the size of the data several times. After introducing variation into the training dataset, the model becomes generalized and, as a result, less prone to retraining. The expanded set of images thus contained 2062 images, including 1083 images of the "Tumor" class and 977 images of the "No Tumor" class. Then it was divided into training (trainset, 1442 images), test (test set, 308 images) and test (valid set, 308 images) samples.

## COMPUTER EXPERIMENTS ON THE APPLICATION OF TRANSFER LEARNING METHODS IN THE RECOGNITION OF BRAIN TUMORS

Computer experiments were conducted on the application of the deep learning transfer strategies proposed above for the recognition of brain tumors on the set of MRI images described above. For this purpose, deep convolutional networks VGG-16, MobileNetV2, Xception and ResNet-50 were chosen as basic training models [17]. First of all, it was necessary to import the weights of the base models from the ImageNet library and "freeze" them by setting the value of the training parameter for each convolutional layer as "False". Next, it was necessary to create a Sequential model from the Keras deep learning library [18]. Then sequentially attach to the frozen layers of the pre-trained modelling a Flatten level layer, two thick layers using functions for activation "relu" and "softmax", correspondingly, separated by thinning layers Dropout(0.1), and a Batch Normalization layer to avoid retraining. In addition, it was necessary to change the output layer of the pre-trained models, since it was configured to classify 1002 image classes, and only two classes ("Tumor" and "No Tumor") were present in the computational experiment. The model constructed in this way was educated with the "binary cross-entropy" function of losing and accuracy, recall, precision, f1-score and AUC (Area Under Curve) accuracy indicators [19, 20]. The beginning keep up of learning was set to 1e−3, and this model was trained over a period of 18 epochs with the batch size = 18 parameters. After training, the best pre-trained model was selected based on the above accuracy metrics obtained in the testing the set.

**Table 1 Performance indicators of basic model training strategies and their fine-tuning**

| Network model | Accuracy tumor | Precision tumor | Recall tumor | f1-metric tumor | AUC macro |
|---|---|---|---|---|---|
| Xception | 92.08 | 92.42 | 95.1 | 93.75 | 95.31 |
| Xception fine-tuned | 96 | 97.7 | 94.01 | 96 | 96.91 |
| ResNet50 | 75.1 | 62.5 | 66 | 69.33 | 72 |
| VGG-16 | 89.41 | 93.1 | 89.2 | 92.1 | 93.4 |
| VGG-16 fine-tuned | 91.12 | 95.42 | 90.24 | 92.32 | 94.11 |
| 2D-CNN | 80.35 | 81.1 | 79.2 | 82.1 | 83.6 |
| MobileNetV2 | 79.21 | 74.64 | 75.52 | 81.66 | 85.41 |

The table 1 shows the classification accuracy indicators on a test set of MRI images of the human brain for two classes ("Tumor" and "No Tumor"). To compare the TL results, a deep convolutional neural network was also built and trained, consisting of three sequentially connected convolutional blocks, each of which contained a 2D-CNN convolutional layer, a Batch Normalization layer and a Dropout layer(0.1). The results of her training are also shown in the table. At this stage of computer experiments, two models were identified that showed the best performance compared to the others. They turned out to be the VG-16 and Exception models with accuracy, precision and recall accuracy indicators equal to 89.40%, 93.2%, 89.2% and 92.09%, 92.42%, 95.2%, respectively.

Further, in the second stage, fine-tuning strategies were implemented for these models. For the Xception model, the 5-unit cross-validation method was applied and estimates of accuracy, precision, recall, and AUC were built. They turned out to be higher than in the basic transfer learning strategy. At the same time, the classification accuracy increased to 96%, precision - 97.7%, recall 94.01%, and the AUC was 96.90%. The classification accuracy of MRI images from the "Tumor" class was 94%, and the classification accuracy of MRI images from the "No Tumor" class was 100%.

Then fine tuning of the base model VGG-16 was carried out as follows. A sequential model of the Keras library was implemented, which previously included the Conv 2D convolution layer with the following parameters: kernel size (3,3), stuffing = 'same', input form = (62, 62, 2). Then the base model VGG-16 is attached with the weights obtained from its training in the previous stage (basic transfer learning strategy). Following this, the Global Average Pooling2D, Group Standardization and Dropout(0.23) layers were successively attached. Finally, fully connected layers such as Dense (units = 510, energizing = 'relu'), Group Standardization, Dropout(0.3) and Thick(1, energizing = = 'sigmoid') were attached to the model.

It was used as an optimizer with the parameter learning rate = 0.001, accuracy metrics accuracy, precision, recall, AUC, number epochs = 98.

As a result of the application of the constructed model for the classification of MRI images of the brain, the following results were obtained: accuracy = 91.12%, precision = 95.42%, recall = 90.24%, AUC = 94.10%. The accuracy of classification of images from the "Tumor" class was 89%, the accuracy of classification of MRI images from the "No Tumor" class was 90%. They are superior to similar ones for the same model, but trained according to the basic learning transfer strategy.

A comparative analysis of the accuracy indicators of the studied deep models and learning transfer strategies in the task of classifying brain MRI images showed that the Xception model as a whole surpasses the VGG-16 model in all accuracy indicators. In addition, the Xception model is less expensive in terms of the amount of memory used and requires less time for training.

## CONCLUSION

The paper investigates the effectiveness of deep neural network learning transfer methods and their fine-tuning as an alternative to deep learning in the area of medical image analysis convolutional neural network training from scratch. The analysis was carried out on sets of MRI images containing images of human brain tumors ("Tumor") and images of the brain of a healthy person ("No Tumor"). Such popular deep neural networks as VGG-16, Xception, MobileNetV2 and ResNet50 were used as basic models of learning transfer strategies.

As the results of computer experiments on the classification of MRI images of the brain using the proposed strategies showed, the VGG-16 and Xception models demonstrated superiority over all deep models trained according to the basic learning transfer strategy, as well as a deep convolutional neural network trained from scratch. If at the stage of applying the basic transfer learning strategy, the accuracy of classification of MRI images by deep models was comparable, then at the stage of applying the fine-tuning strategy, they significantly exceeded them. In general, we can conclude that the proposed strategies for training deep models allow us to obtain more accurate results.

Classification of the classification problem under study compared to deep model training from scratch. Thus, based on the results of conducted numerical experiments and the obtained estimates of the performance of deep learning models, it can be concluded that the methods of fine-tuning and transferring training on deep neural networks are more effective for detecting brain tumors from its MRI images, carrying out their significantly better convolutional neural networks learned from scratch, and surpassing them with limited opportunities to increase the size of data.

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