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# MAIN TRENDS IN SCIENCE, TEACHING AND MODERN LEARNING

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# REVIEW OF THE RESNET-50 CONVOLUTIONAL NEURAL NETWORK ARCHITECTURE

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ResNet is a deep convolutional neural network architecture developed by the Microsoft Research team specifically for image processing [1-7].

The primary feature of this architecture and its main advantage is the use of residual learning, which avoids learning at each step [8, 9]. This approach enables you to train networks with a large number of layers while avoiding the phenomenon of gradient decay, which occurs when the learning rate of a neural network slows down or stops at a significant number of epochs [10-18].

Another advantage of the ResNet architecture is its high training accuracy and flexibility in scaling, which is achieved through the use of bottleneck residual blocks. Thus, the model can be expanded and modified by adding new layers. Models such as DenseNet, Wide ResNet, ResNeXt, and others were also built on this basis.

Among the most fundamental disadvantages of this architecture is its high computational complexity. Since the models of this architecture are typically quite deep, there is an issue with calculating a large number of parameters. Because of this, they are pretty slow, which makes them difficult to use in real-time systems such as mobile applications. In addition, the process of training such models for these reasons also requires a significant amount of time to obtain high accuracy.

Additionally, during training, a problem may arise a lot when the transfer of residual information slows down the learning process, as new layers make only minor changes or don't make any at all, relying on data from previous epochs. This can also significantly slow down the learning process and lead to a limitation in the neural network's efficiency.

The architecture of ResNet-50, which will be discussed below, consists of 50 layers distributed across several levels, including the last one, which is represented by a fully connected layer.

ResNet-50 has six levels in total, of which:

– Conv1 is the initial level;
– Conv2_x has three bottleneck residual blocks;
– Conv3_x has four bottleneck residual blocks;
– Conv4_x has six bottleneck residual blocks;
– Conv5_x has three bottleneck residual blocks;

– The sixth level is a combination of the global averaging functions, the fully connected layer, and the Softmax function.

The first level of the model (Fig. 1) is the initial one. It acts as a stage of preparing the input data for further processing. First, the basic features are extracted from the image using a 7×7 convolution, and the size is reduced by half. Thus, the edges of objects and color transitions are immediately detected. After that, normalization functions are applied to the obtained result to stabilize the output of the applied convolution and the ReLU activation function to add nonlinearity and, as a result, achieve more flexible classification of the model.

**Figures 1-4 are the authors' own, created during this research.**

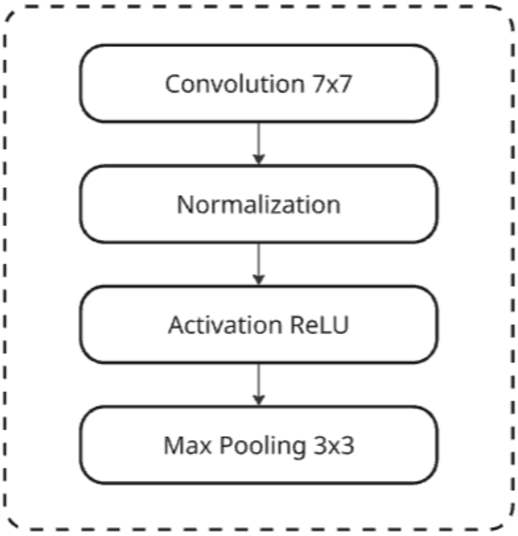


**Figure 1** – Structure of level Conv1

The final stage involves applying the maxpool function. It performs a 1×1 convolution, while extracting the maximum number from the region. This reduces the amount of data that needs to be processed at the next level and highlights the most contrasting areas.

The structure of subsequent levels (Fig. 2), except for the last one, differs only in the number of narrowed residual blocks used. Also, at the Conv2_x level, there is no preliminary reduction in the image size, since convolution has already been applied to the input image at the final stage of the Conv1 level. Thus, the levels consist only of a preliminary convolution of the image by half and the subsequent application of narrowed residual blocks to it. After the blocks, there are no additional normalization and activation functions, since they are already included in the block structure.

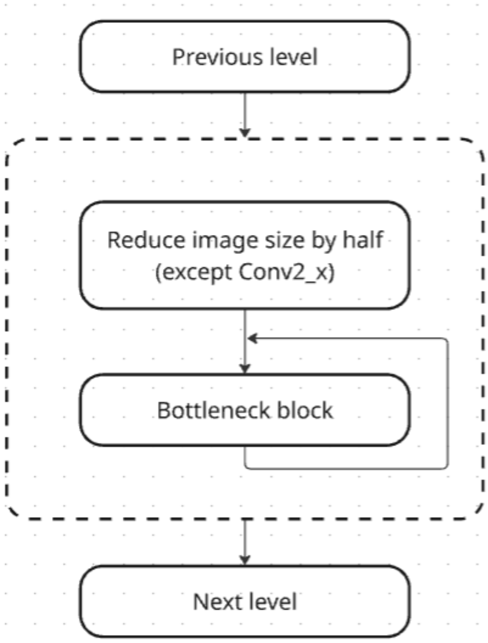


**Figure 2 –** The structure of Conv2_x, Conv3_x, Conv4_x and Conv5_x levels

The last level is the output (Fig. 3). Global averaging is applied to the feature map obtained from the previous levels, which converts it into a vector by taking the average for each channel. After that, the resulting vectors are transferred to the fully connected layer, where they are combined into a single vector. The final stage involves applying the SoftMax function.

A key feature of the ResNet-50 model and the ResNet architecture as a whole is the use of tapered residual blocks (Fig. 4) as the primary means of feature extraction and classification. By adding the input tensor to the result obtained after convolution, the results become more gradual and contribute to the stabilization of the results during training.

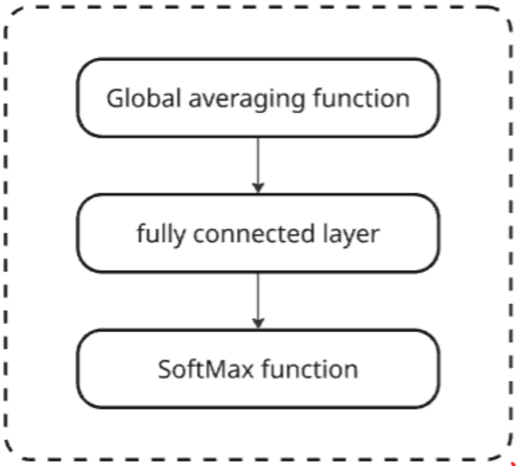


**Figure 3 –** The latest level of ResNet-50

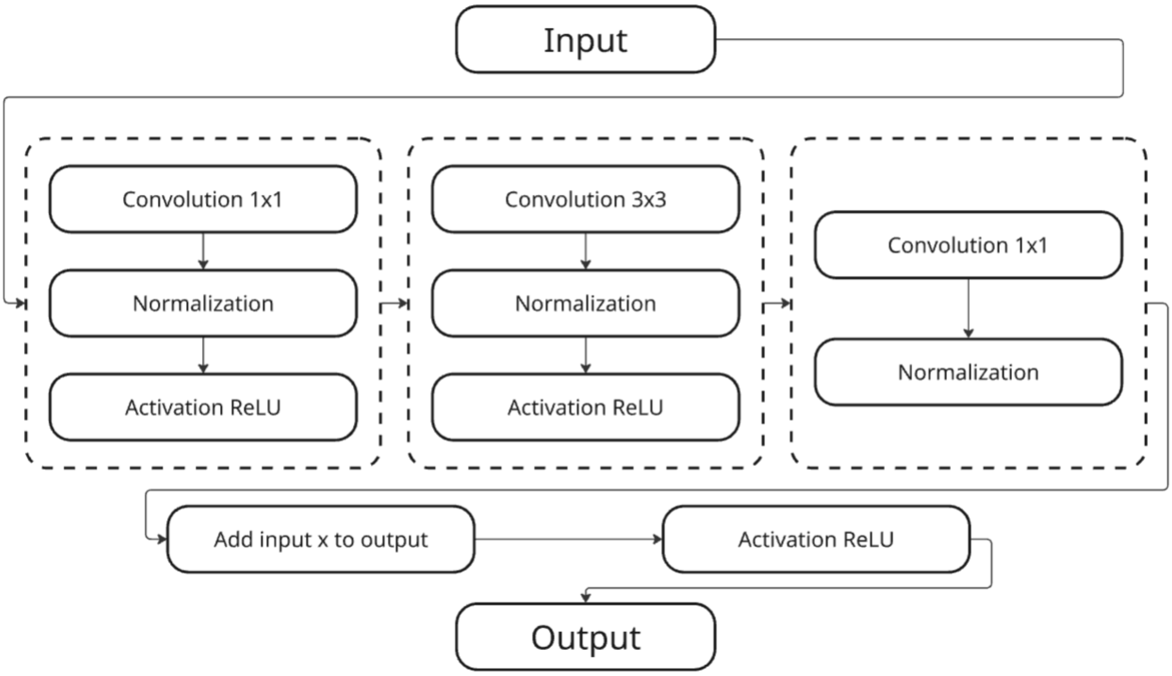


**Figure 4** – Scheme of the bottleneck residual block

The tapered residual block can be represented as the formula:

$$y = F(x, \{W_1, W_2, W_3\}) + x, \quad (1)$$

where $x$ is the input of the block, $F(x, \{W_1, W_2, W_3\})$ is the function of the residual block (consists of 3 convolutional layers: 1×1, 3×3, 1×1), $y$ is the output of the block.

In turn, the function of the residual block can be represented by the formula:

$$F(x) = W_3 * BN(\sigma(W_2 * BN(\sigma(W_1 \cdot BN(x))))), \quad (2)$$

where $W_1$ is the kernel of the first layer 1×1, $W_2$ is the kernel of the second layer 1×1, $W_3$ is the kernel of the third layer 1×1, · is the convolution operator, *BN* is the normalization function, σ is the ReLU activation function.

It should be noted that the output data of the residual block function are comparable to the input data since the residual tensor is subsequently added to the obtained one.

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