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DIAGNOSIS OF COVID-19 DISEASE BASED ON A MODIFIED CONVOLUTIONAL NEURAL NETWORK ON THE EXAMPLE OF LUNG X-RAYS

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ABSTRACT

As a result of the study, a machine learning model based on a modified convolutional neural network was developed to diagnose COVID-19 lesions from lung X-rays. Due to the improvement of the network architecture, it was possible to obtain a classification accuracy of 91%. The developed model can be used in the field of health care to assist medical staff in the analysis of X-rays, which will reduce the likelihood of medical error.

Keywords: pattern recognition, COVID-19, classification, neural network, perceptron.

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INTRODUCTION

Over the past 3 years, humanity has faced the epidemic of COVID-19, the spread of an infectious disease caused by the SARS-CoV-2 virus. The pandemic has led to serious socio-economic problems around the world, as well as the need to develop new medical technologies [1].

Lung radiography and computed tomography are performed to diagnose atypical pneumonia in COVID-19. Analysis of images allows the doctor to assess the degree of lung damage, predict possible deterioration, and develop a strategy for patient care [2]. However, such a diagnosis is characterized by a human factor: the doctor makes mistakes. This is especially evident under heavy load.

Promising in terms of diagnostics is the already-known technology of using machine learning models for pattern recognition. Thus, the neural network created by the Australian startup DetectED-X to detect cancer is used to diagnose COVID-19 [3].

Next, the problem of developing a system that can diagnose COVID-19 on X-rays of patients will be considered and solved, with an overview of different machine learning algorithms: simple and convolutional neural networks, the support vector machine, and decision trees.

Classification - assignment of the presented objects to certain classes by applying the known rules of classification [5].

ANALYSIS OF LITERATURE DATA AND PROBLEM STATEMENT

The classification problem can be formally defined as the problem of estimating the label y for the input vector x of dimension *K*, where

$$x \in X \subseteq R^K \tag{1}$$

and

$$y \in Y = \{C_1, C_2, ..., C_q\} \tag{2}$$

This problem is solved by using a rule or classification function which can predict the labels of new vectors. For managed learning algorithms, which are discussed below, a training data set of N points represented by D is provided, from which g, can be corrected [4].

$$g : X \to Y, \tag{3}$$

$$D = \{(x_i, y_i), i = 1, ..., N\} \tag{4}$$

Further, it is necessary to consider various algorithms of machine recognition of images and to estimate them on criteria of speed of work and accuracy of classification. The last criterion is key because the speed of the algorithm can vary depending on the equipment used, and accuracy - no.

Decision trees, another machine learning algorithm, are discussed in the articles [5, 6]. Trees are used in the classification of images. Thus, the article [5] proposes a classification of landscape points based on satellite images. [6] Considers the possibility of pre-obtaining abstract characteristics of images and subsequent use of trees on processed data to obtain a model with high classification accuracy.

Among the advantages of the method are the transparencies of the final model, fairly high results of image classification after obtaining abstract

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characteristics, as well as the lack of need to normalize the input data.

Disadvantages include the need for significant pre-processing of input data and the frequent occurrence of the problem of retraining the model.

In articles [7, 8] the support vector machine is considered. In particular, in [7] the binary classification of images after simple preliminary processing is offered. Together with the use of the reference vectors method, it was possible to obtain fairly high classification accuracy. In [8], due to the use of the support vector machine together with a complex algorithm of pre-processing of input data for the classification of images of land plots, it was possible to achieve a fairly high classification accuracy of 90.6%.

Among the advantages of the algorithm are high results of image classification after obtaining abstract characteristics, and the ability to efficiently process large enough dimensions of data.

The need for significant pre-processing of input data and the lack of transparency of the model are the main disadvantages of the support vector machine.

Neural networks, in particular convolutional neural networks, and their modifications are considered in [9] - [11]. The use of so-called convolutional neural networks makes it possible to obtain a surprisingly high accuracy of image classification. Thus, the convolutional neural network proposed in Article [9] has reached an accuracy of 75% on a data set containing 60 thousand images. Article [11] discusses neural networks based on the VGG16 and VGG19 architectures used to classify X-rays to diagnose pneumonia. The authors of the article managed to achieve a model accuracy of 95.7%. The article [10] proposes the use of modified neural network architectures Xception and ResNet50V2 directly for the classification of X-rays with suspected COVID-19, which allows to achieve an accuracy of 91.4%.

The advantages of neural networks are the absence of the need for pre-processing, as neural networks work with raw data. In addition, using this method, it is theoretically possible to achieve a level of accuracy close to this level in humans.

The disadvantages of this method include the high cost of computing resources for training and operation of the neural network, as well as the opacity of the model.

Methods such as decision trees make it possible to obtain relatively large values of recognition accuracy, but at the same time are transparent. That is, the decisions of these models on the classification of an object are based on a human-readable principle. Undoubtedly, this can be an important factor in choosing a method of lung imaging, as it will allow the radiologist to understand the key criteria for diagnosing COVID-19 and test the algorithm with supporting data.

On the other hand, decision trees as well as the reference vector method require pre-processing of data. Such processing will consume additional computing resources, and its implementation will require extensive research or even develop another model of machine learning.

In addition, neural networks have the potential to recognize deeper patterns in the input data and achieve higher accuracy in the classification of patients' lung images. This is indicated by the successful results described above for processing large amounts of input data using convolutional neural networks.

Of course, complex neural networks have a significant disadvantage - they lose to all considered algorithms in speed. As shown in the paper, which discusses the efficiency and speed of different machine learning algorithms in the classification problem, convolutional neural networks can take hundreds of times longer than decision trees on a single training set [12].

Given all the factors, it can be concluded that neural networks are the best choice as a machine learning model for the diagnosis of COVID-19 based on the classification of images of patients' lung images. The final analysis of the considered algorithms is given in Table-1.

Table-1. Comparison of considered algorithms.

Method name	Raw data[a]	Transparency[b]	Learning resources[c]	Resources for work[d]	Tendency to relearn [13]	Time[e]
Decision trees	No	Yes	Yes	No	High	0.07
SVM	No	No	Yes	No	Low	18.12
Neural networks	Yes	No	Yes	Yes	Low	33.5

[a]Ability to process raw data
[b]Transparency of the classification principle
[c]The need to spend significant resources on model training
[d]The need to spend significant resources on the work of the model after training
[e]Time for data processing from the reference set [12], c

Given the above characteristics of different machine learning algorithms, as well as the results of their testing below, it is necessary to use a model that differs from the standard ones. As will be shown below, a modified convolutional neural network can achieve recognition accuracy greater than the accuracy of standard algorithms in this problem.

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DEVELOPMENT OF A MACHINE LEARNING MODEL

Open source data were used for training and testing of all algorithms [14]. Images have been compressed to 200 by 200 pixels to save resources, including memory and CPU time. This made it possible to train models using much larger data sets.

Two sets of input images were formed to test the model: a smaller one with 300 images for learning, 150 for testing, and a larger one with 1,200 images for learning and 300 images for testing.

The Accord.NET library was used to create models based on the support vector machine, decision trees, and simple neural networks.

Because none of the above models can work effectively with raw image data, the Bag of visual words algorithm from Accord.NET was used to extract fixed-length vector data from raw data. Within the framework of this algorithm, the method of local binary templates was used directly to extract features, and binary splitting or clustering by the k-means method was used to reduce the dimensionality of the feature vector.

The best test results of each of the methods are given in Table-2. It can be seen that none of the methods was able to achieve an accuracy of more than 85%.

Table-2. The best results of traditional methods.

Method name	Best accuracy on a larger set	Best accuracy on a smaller set
SVM	85%	78.6%
Decision trees	66.3%	65.3%
Simple neural network	53.33%	36.66%

To create a more complex, multi-layered convolutional neural network, the Keras Python library was used, which is an add-on to another library, TensorFlow.

A convolutional neural network was developed, the configuration of which is given in Table-3. It consists of 8 layers, and only 4 of them have parameters to be studied. Small neural networks with a similar architecture are commonly used to classify simple sets of images (including handwritten numbers) into several classes. Conditionally call this modification "Simple".

The ReLU function is used as the activation function. The categorical cross-entropy function is used to assess the accuracy of the model. The frequency of coincidence of the value predicted by the model with the true value was used as a measure of accuracy.

The outer layer of rescaling accepts raw image data and translates the saturation value of each pixel in the range from 0 to 1.

The three original neurons correspond to the probability that the image under consideration belongs to one of three classes: COVID-19 lesions, normal lung status, and other diseases.

As a result of testing, the first modification "Simple" was able to achieve a classification accuracy of 75.17% for smaller and 84.33% for larger sets.

Table-3. Configuration of the first "simple" modification of the rolled neural network.

Layer type	Initial form	Number of parameters
Rescaling	(None, 299, 299, 3)	0
Convolutional layer with 8 3x3 filters	(None, 299, 299, 8)	224
Aggregation layer	(None, 149, 149, 8)	0
Convolutional layer with 16 3x3 filters	(None, 149, 149, 16)	1168
Aggregation layer	(None, 74, 74, 16)	0
Flatten	(None, 87616)	0
A fully connected layer of 64 neurons	(None, 64)	5607488
A fully connected layer of 3 neurons	(None, 3)	195

As can be seen from the test results, the architecture of the "Simple" modification is not complex enough, so the network is not able to find deep enough links between input and output data and achieve classification accuracy of at least 85% on a larger data set. It is necessary to increase the size of the neural network.

A second, more complex modified convolutional neural network was developed. Conditionally call it a "complicated" modification. Its structure is given in the table. 4. In the second modification, the convolution layer was removed from 8 3x3 filters and the next aggregation layer. A convolution layer with 32 3x3 filters, a convolution layer with 64 3x3 filters, and two aggregation layers following them have also been added. Finally, a dropout layer with an exclusion probability of 0.1 has been added. The full layer of 64 neurons increased to 128 neurons.

As a result of testing, the second modification "Complicated" was able to achieve a classification accuracy of 79.19% for smaller and 85.67% for larger sets.

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Table-4. Configuration of the second "complex" modification of the convolved neural network.

Layer type	Initial form	Number of parameters	Comment
Rescaling	(None, 299, 299, 3)	0	
Convolutional layer with 8 3x3 filters	(None, 299, 299, 8)	224	Layer removed
Aggregation layer	(None, 149, 149, 8)	0	Layer removed
Convolutional layer with 16 3x3 filters	(None, 299, 299, 16)	448	
Aggregation layer	(None, 149, 149, 16)	0	
Convolutional layer with 32 3x3 filters	(None, 149, 149, 32)	4640	Layer added
Aggregation layer	(None, 74, 74, 32)	0	Layer added
Convolutional layer with 64 3x3 filters	(None, 74, 74, 64)	18496	Layer added
Aggregation layer	(None, 37, 37, 64)	0	Layer added
Dropout layer with a probability of exclusion of 0.1	(None, 37, 37, 64)	0	Layer added
Flatten	(None, 87616)	0	
A complete layer of 128 neurons in size	(None, 128)	11214976	The number of neurons in the layer increased to 128
A fully connected layer of 3 neurons	(None, 3)	387	

Some changes have been made to reduce the effect of retraining and overall optimization for the neural network.

X-ray images are now considered as a two-dimensional array of real numbers, rather than vectors with three values. X-rays are monochrome in nature, so there is no need to process each of the channels separately. Only the Adam learning algorithm is used, and the learning speed is halved. This will help reduce the effect of retraining.

Some changes have been made to the network structure. In all convolutional layers, the sizes of filters have been changed from 3x3 to 8x8, and a convolutional layer with 8 8x8 filters, a convolutional layer with 128 8x8 filters, and 2 aggregation layers following them have been added. In addition, one full-length layer of 128 neurons was replaced by three consecutive full-length layers of 2,048 neurons.

The configuration of the third modification is given in Table-5. Conditionally call it "Complex".

As a result of testing, the third modification "Complex" was able to achieve a classification accuracy of 68.46% for smaller and 87.33% for larger sets.

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Table-5. Configuration of the third "complex" modification of the convolved neural network.

Layer type	Initial form	Number of parameters	Comment
Rescaling	(None, 299, 299, 1)	0	
Convolutional layer with 8 8x8 filters	(None, 299, 299, 8)	520	Layer added
Aggregation layer	(None, 149, 149, 8)	0	Layer added
Convolutional layer with 16 8x8 filters	(None, 149, 149, 16)	8208	The filter has been resized to 8x8
Aggregation layer	(None, 74, 74, 16)	0	
Convolutional layer with 32 8x8 filters	(None, 74, 74, 32)	32800	The filter has been resized to 8x8
Aggregation layer	(None, 37, 37, 32)	0	
Convolutional layer with 64 8x8 filters	(None, 37, 37, 64)	131136	The filter has been resized to 8x8
Aggregation layer	(None, 18, 18, 64)	0	
Convolutional layer with 128 8x8 filters	(None, 18, 18, 128)	524416	The filter has been resized to 8x8
Aggregation layer	(None, 9, 9, 128)	0	
Dropout layer with a probability of exclusion of 0.1	(None, 9, 9, 128)	0	
Flatten	(None, 10368)	0	
A complete layer of 128 neurons in size	(None, 128)	11214976	Layer removed
A fully connected layer of 2048 neurons	(None, 2048)	21235712	Layer added
A fully connected layer of 2048 neurons	(None, 2048)	4196352	Layer added
A fully connected layer of 2048 neurons	(None, 2048)	4196352	Layer added
A fully connected layer of 3 neurons	(None, 3)	6147	

Such a small increase in accuracy on a larger set, and virtually no on a bag, with a significant increase in neural network complexity, may indicate that much more input is needed to overcome retraining and achieve an accuracy of 90% or more.

To test the hypothesis, we will teach a "Complex" network on a data set of 10,500 X-rays (3,500 images per class) obtained from the same source as the previous data sets. 20% of images will be used for validation.

As a result of the last testing, the network reached an accuracy of 91.19%, which proves the previously stated assumption.

RESULTS

Table-6 presents a final comparison of the effectiveness of different models of machine learning on two data sets. Although the convolutional neural network is only a few percent ahead of the reference vector method, this model has much greater potential, which is manifested in the further increase of training sets, as shown above.

Table-6. The best results of different methods.

Method name	Best accuracy on a larger set	Best accuracy on a smaller set
SVM	85%	78.6%
Decision trees	66.3%	65.3%
Simple neural network	53.33%	36.66%
Convolutional neural network	87.33%	79.19%

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CONCLUSIONS

During the work the classical methods of machine learning were analyzed: decision-making trees, the support vector machine, as well as simple neural networks. However, much better results and greater potential in solving this problem showed models based on convolutional neural networks.

An accuracy of 87.33% was obtained for the convolutional neural network. It was also found that the model has the potential to increase accuracy. This was demonstrated when training a modified network on input data from 10,500 images when the model reaches an accuracy of 91.19%.

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