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Machine learning in lung lesion detection caused by certain diseases

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The work highlights neural network applications to medical images, namely X-ray images. An overview of neural networks used to analyze medical images was conducted. Such a neural network has been implemented and tested on third-party images.

Keywords: *image classification; convolutional neural networks; deep learning; chest X-ray radiography.*

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1. Application of machine learning to medical image analysis

In the last decade, machine learning has begun to gain more and more popularity and today occupies one of the leading positions in the field of information technology, e.g. [1,2]. The volume of digital data used by humanity is increasing every day, and that is why the demand for automatic data analysis for the further development of technological progress has emerged. The main objective of machine learning is to train the model in such a way that it can independently, without a person's intervention, make decisions based on its prior experience in solving tasks.

It seems that for the previous decade, the greatest scientific progress has been made in the field of computer vision. Such findings get applied in the real world and even surpass a person in solving visual tasks. There are many algorithms and tools for image analysis, but in recent years, machine learning algorithms have shown the best results in almost all computer vision tasks. In 2012, Geoffrey Hinton, Alex Kryzhevsky, and Ilya Sutskever proposed an approach to image classification based on neural networks. Neural networks, based on the biological structure of the human brain, exceed other machine learning algorithms in terms of their computing power. Their classification algorithm, the convolutional neural network AlexNet [3], has almost doubled the state-of-the-art computer vision models at the time, making a breakthrough in data science and, in particular, in semantic image analysis. Currently, convolutional neural networks (CNN) reside at the forefront of almost all pattern recognition and machine vision tasks, such as image classification, segmentation, and object detection.

One of the fields that start to adapt machine learning to their tasks is Medicine [4]. The most popular task of machine learning in medicine is medical image analysis. It is keen on providing a more efficient diagnostic and therapeutic process for radiologists and other physicians. The active development of modern medical diagnostic systems causes a constant increase in the number of digital images received in various medical institutions. For effective use in the diagnostic process, these images must be immediately analyzed.

For example, in December 2019, the coronavirus infection (COVID-19) was discovered, and since then the disease has spread around the world. As in May 2022, there were 550 million confirmed cases of COVID-19 worldwide, and 6.24 million people died [5]. To diagnose pneumonia, X-ray confirmation of focal infiltration of lung tissue and at least two other clinical signs are required. Thus, diagnosis is not based only on X-ray imaging, but it is desirable. In addition, a chest X-ray is often useful for monitoring treatment outcomes and comorbidities in critically ill patients [6]. In the spring of 2019, quarantine was introduced in most countries; the number of patients was so large that the healthcare system could not cope with the excessive number of disease cases. The models for the most severe cases determination would have helped doctors to classify the most severe patients faster, which would have reduced the burden on the healthcare system.

As the most common means of examination in medical practice, the chest X-ray has important clinical significance for the diagnosis of the disease. Thus, the automatic detection of chest disease based on chest X-rays has become one of the current topics of research.

Artificial intelligence (AI) and machine learning are successfully being used in medicine and solve a wide range of problems: from identifying pathology on X-ray images to diagnosing and drawing up a treatment plan based on data from the patient's medical history. The algorithms of AI are based on medical data analysis and their processing in accordance with given algorithms. Currently, not only the data of an objective examination and the patient's history are being analyzed, but also the analyses results and examinations, gotten by medical equipment [7].

2. The convolutional neural networks usage for the analysis of radiological images

Radiology is a very promising field and the information obtained from images is very useful and important for diagnosis. It is been one of the first areas in medicine where AI was used for image analysis. As soon as it became possible to scan and download medical images into a computer, researchers tried to build a system to automate the analysis of such images. Initially, from the 1970s to the 1990s, medical image analysis was performed using a series of low-level pixel processing applications such as edge and line detector filters, region selection by joining pixels with similar characteristics (region growing), and mathematical modeling to build a rule-based system that could only solve a specific task. Towards the end of the 1990s, tutored learning techniques became popular and became increasingly popular in the field of medical image analysis. Doctors got able to process images in automatic mode, filter the norm, and provide conclusions only for images marked by the program as pathological [8].

The field of image recognition and convolutional neural networks have made great strides in recent years. Computer algorithms do a good job of identifying edges and important features to analyze the image and get the best result. In some tests, image recognition algorithms outperformed humans. The most successful type of image analysis model to date is convolutional neural networks. The medical image analysis community has taken note of these key developments. However, the transition from systems that used hand-crafted features to systems that learn features from the data itself has been gradual. The referrals to Deep Learning technics in medical image analysis first have begun to appear in workshops and conferences, and then in journals.

Accordingly, the idea has arisen to apply AI to the field of image recognition where doctors do image recognition, namely the analysis of images and, to begin with, X-rays. X-rays are used to diagnose a wide range of diseases and injuries: lung injuries (pneumonia, cancer), fractures, and other bone injuries, etc. It is important that in the diagnosis of some of these diseases, the X-ray picture and its interpretation is the main tool in making the diagnosis.

Deep learning is used in the analysis of medical images to solve the following problems [9]:

- *Classification*: This was one of the first areas where deep learning has been applied to medical image analysis. Object or lesion classification usually focuses on classifying a portion of a medical image into two or more classes.
- *Detection*: localization of anatomical objects such as organs/lesions is an important part of the preprocessing of the segmentation task.
- *Segmentation*: Segmenting organs and other structures in medical images allows for quantitative analysis related to shape, size, and volume. The task of segmentation is usually defined as identifying a set of pixels that define a contour or analyzed object.
- Content-based image retrieval is a method of searching for information in large databases based on similar disease histories.
- Image generation and enhancement is another task that uses deep learning to improve image quality, image normalization, and pattern detection.
- Combining these images with reports is a task that has a very serious practical application. Two distinct areas of research stem from this: using reports to improve image classification accuracy and generating textual reports from images.

Artificial intelligence continues to adapt to healthcare challenges and will have a major impact on every aspect of primary care. Computer programs with AI support will help doctors quickly and accurately identify patients who need additional attention. By analyzing patient data, AI models will help doctors identify early symptoms of certain diseases, such as heart disease or diabetes, before they become more serious.

3. An overview of neural networks leverage for medical image analysis

The use of artificial intelligence, in particular deep learning, has become possible because of the growth of the volume of labeled data, as well as the increase in computing power and the ability to use cloud storage. All of this, in turn, will help doctors quickly and accurately interpret images, healthcare systems improve workflow and reduce medical errors, and allow patients to process their own data as an analog of more accessible diagnostics. The neural networks leverage in medicine will reduce the number of serious diagnostic errors and errors in treatment, reduce the cost of resources, and allow achieving a more efficient work process, as well as increasing the time spent by a doctor with a patient.

In the future, a doctor of almost every specialization will be able to leverage AI technologies, in particular the deep learning ones. It implies image recognition using deep neural networks that can help to interpret medical scans, pathology slides, skin lesions, retinal images, electrocardiograms, and other vital signs [10].

Scientists have already been trying to use neural networks to classify and analyze medical images. The medical journal Frontiers in Medicine [11] compares the performance of 17 available deep-learning algorithms for determining the presence or absence of COVID-19. The best results have been achieved using the pre-trained DarkNet-19 neural network. In an article in the journal Multimedia Tools and Applications [12], the performance of using the AlexNet and VGGNet16 models in combination with the support vector method was compared. In the NPJ Digital Medicine article [13], AlexNet, VGG, GoogLeNet, ResNet, and DenseNet have been trained and tested on the training and validation sets, respectively, and then were evaluated on the test set based on radiologists' labels.

Thus, these works give examples of the application of transfer learning for the classification of medical images. Transfer learning is a machine learning method that is the principle of applying a model developed for a specific task as a starting point for a model for another task. This approach is popular in deep learning because it enables the rapid creation and training of new models. Other works [14] suggest using a simple convolutional neural network optimized for the task of detecting tuberculosis. The architecture of the proposed network consists of 5 convolutional blocks followed by a "Global average pooling" layer that compresses each feature map to its average value. This is followed by a fully connected layer with a "Softmax" activation function with two outputs. Each convolutional block contains two 3×3 convolutions with the ReLU activation function, followed by a "Max pooling layer". The pool size is 3×3 with a step of 2, the same as in AlexNet.

Many radiology images and their data sets are available online, but not all are labeled by radiologists. Thus, there is a dearth of validated data, and not all hospitals upload patient data online as a public dataset. To ensure that the model learns to classify based on relevant biological features, the dataset used to train the model must be pre-processed when building the model. To expand data, augmentation is used, which consists in various types of data transformations.

An article in the journal IJSRST [15] proved that the model works best when using image preprocessing techniques. The preprocessing technique that produced the best results was to use global histogram smoothing. Histogram smoothing is a non-linear process that aims to reshape an image in such a way as to create an image with a flatter histogram. This method boosts image contrast by comparing image pixels with similar contrast values and distributing their intensity on a histogram [16]. The work of Plos One magazine [17] proved the effectiveness of using histogram alignment in combination with Gaussian blurring.

Thus, convolutional neural networks trained from scratch or using transfer learning approaches are used to analyze medical images. Also, pre-processing of images is used to improve the results, and augmentation is used to prevent overtraining of the model.

4. A neural network assembly for the analysis of X-ray images of the lungs

To build a neural network, the dataset "Chest X-Ray Images (Pneumonia)" has been used, which presents X-ray images of healthy lungs, as well as lungs affected by pneumonia [18]. The set was taken from the analytics and predictive modeling competition platform Kaggle, which also features datasets. The set is immediately divided into training and test sets. Examples of images of normal and pneumonia-affected lungs from these sets are shown below (Figure 1).

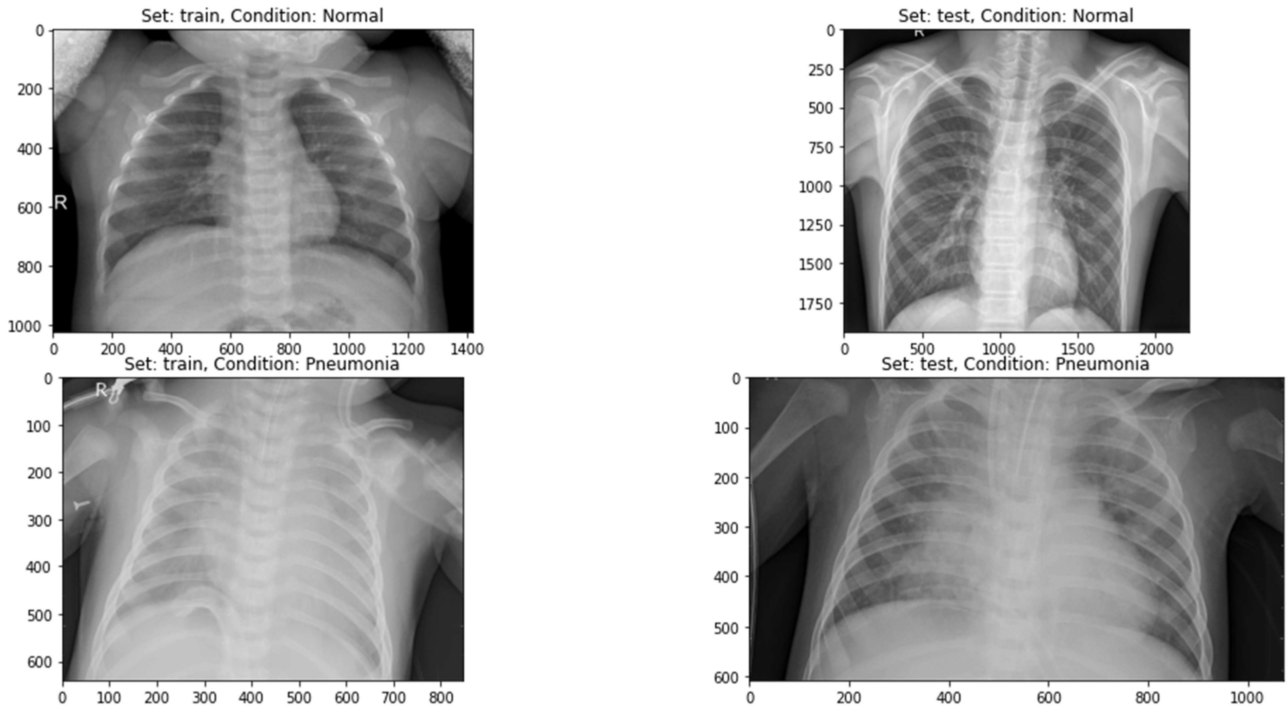

Fig. 1. Examples of images for training and test data sets.

Figure 1 shows that the images in the dataset are of different sizes. Thus, before feeding the data to the neural network, the images were resized to 300 by 300 pixels. In addition, the transformations that will be performed on the images were specified to achieve better results. The global histogram alignment was applied to the training and test sets, which increased the contrast of the images (Figures 2 and 3).

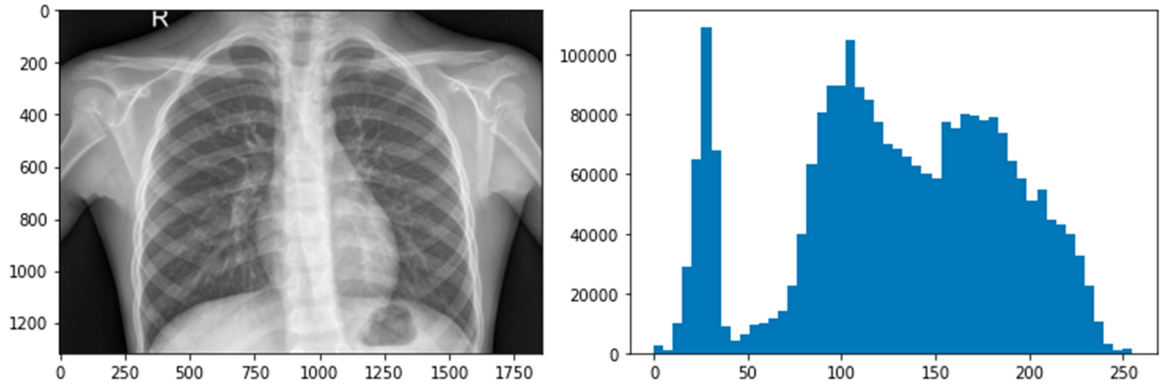

Fig. 2. Image and its histogram before the global histogram alignment.

The image was represented in the form of tensors, which is the basic unit of working with data in PyTorch. And after that, normalization with mean value and standard deviation was applied:

$$output[channel] = \frac{input[channel] - mean[channel]}{stg[channel]}.$$

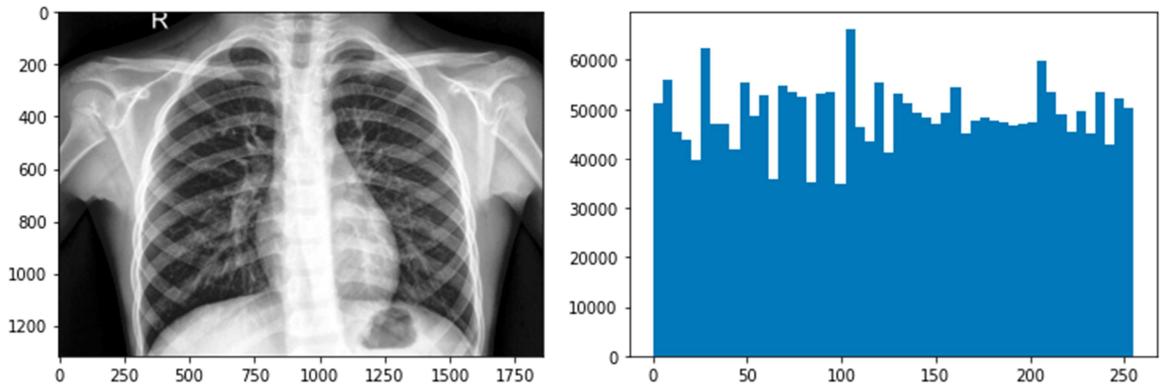

Fig. 3. Image and its histogram after the global histogram alignment.

The average value for each channel is 0.5, and the standard deviation for each channel is 0.5. The result obtained after applying normalization is in Figure 4.

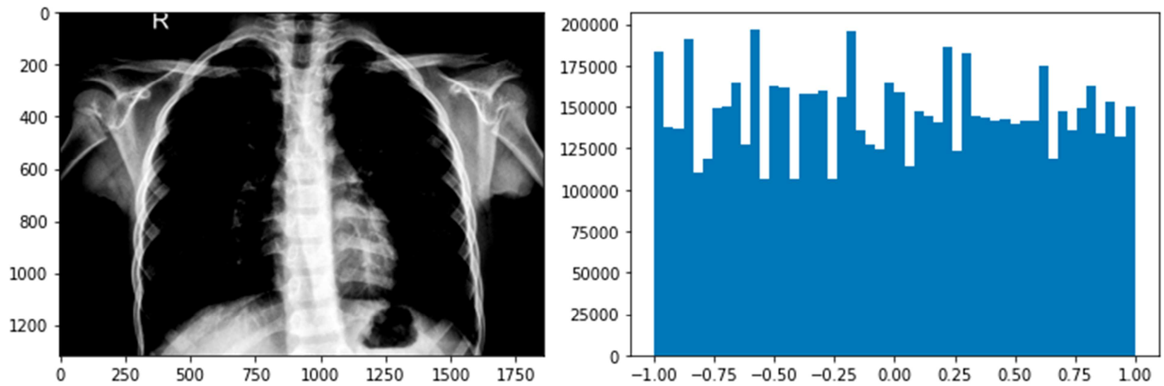

Fig. 4. Image and its histogram after applying normalization.

In addition, Gaussian blurring was applied to the images of the training and test sets, which is used to reduce image noise and unwanted details that can negatively affect the results of the neural network [17].

The dataset "Chest X-Ray Images (Pneumonia)" contains 5216 images in the training set, of which 1341 are healthy lungs and 3875 are affected by pneumonia, and 624 images in the test set, of which 234 are healthy and 390 are affected by pneumonia, which is considered an insufficiently complete data set.

In order to expand the training set, data augmentation was applied, which is an increase in the data set by modifying existing ones. To do this, we used the rotation of the image by an angle in degrees, an affine transformation, which, when the *degrees* parameter is set to zero, and the *translate* is different from zero, will allow you to shift the image vertically and horizontally. Also, the image has been cropped in the center and flipped horizontally randomly with a given probability.

Thus, after applying all transformations to the input, the model will receive less uniform data. As a result of the transformations, an image with 3 channels measuring 300 by 300 pixels has been obtained.

Since the data set was immediately divided into training and test sets by folders, the "train" and "test" data sets have been created using the ImageFolder class, and transformations were applied to them. The DataLoader class was used to load data in batches. The number of images in each batch can vary, the best results were achieved with batch_size = 128. The images in the training sample are shuffled, using the shuffle=True option, so that the model will be trained evenly on all types of data, rather than initially on images with healthy lungs, and then on the ones, affected by pneumonia.

Below are 16 images with corresponding labels from the training set, which after applying the transformations will be submitted to the neural network for training (Figure 5).

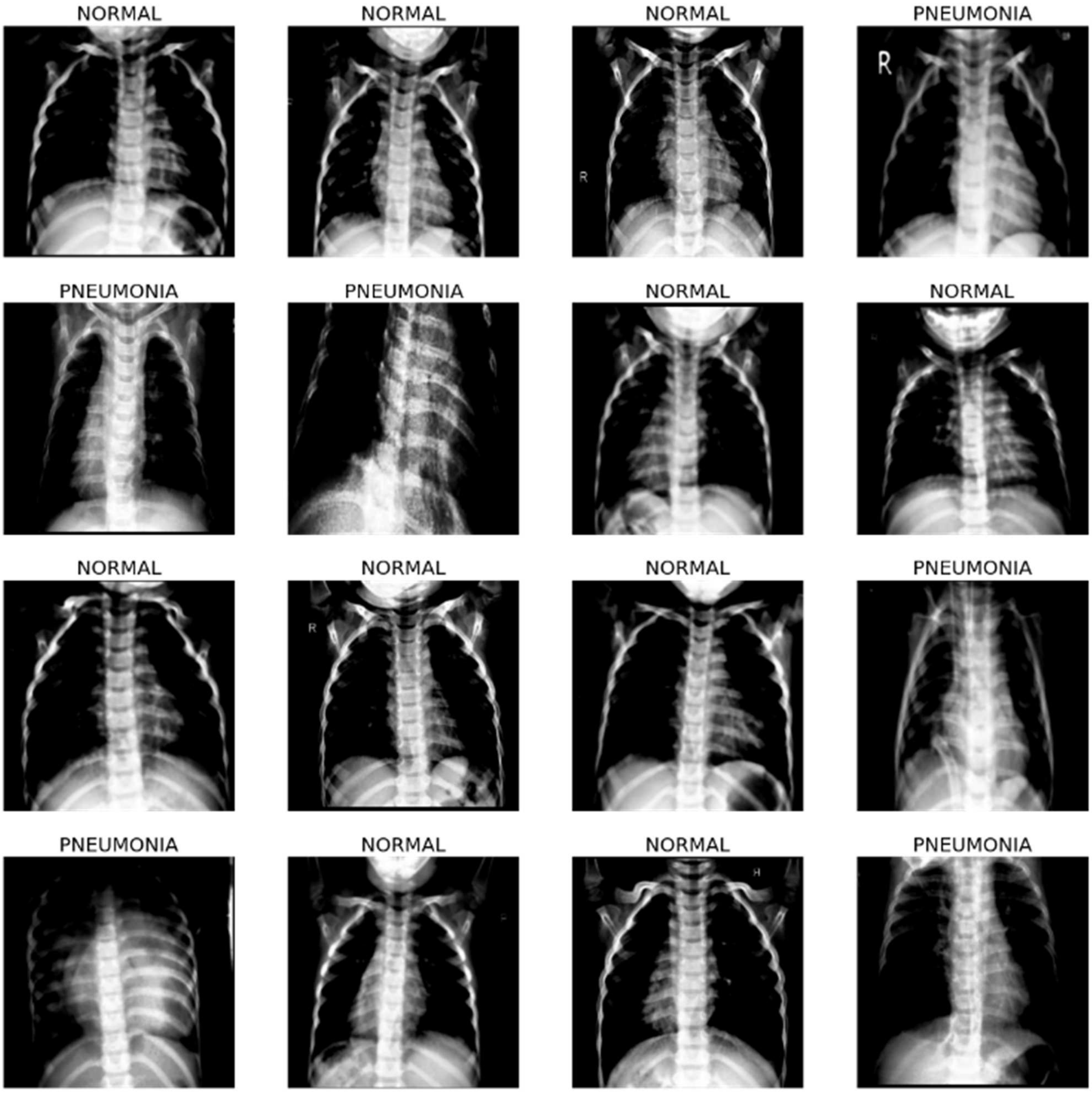

Fig. 5. Examples of images from the Training set after applying transformations.

To build the neural network, the ChestX_raysNet class was created, which inherits from the nn.Module, the base class for all neural network modules in PyTorch. In the ChestX_raysNet class, 5 convolutional layers with a 3 by 3-pixel filter and two linear layers were implemented. Convolutional layers extract meaningful information from the input data, and linear layers, in turn, act as a classifier. A ReLU activation function, a rectified linear activation whose slope is non-zero over much of the input space, is applied to each layer except the last one, which allows propagation of non-zero gradients and prevents the decaying gradient problem. After each of the 5 convolutional layers, the "Max pooling" layer is implemented. As a result, 64 activation maps with a size of 7 by 7 pixels were obtained. Thus, the first linear layer receives $64 \times 7 \times 7$ neurons, and at the output, we will have only 2 neurons, since the classification into two classes is implemented (Figure 6).

The loss function in the neural network determines the difference between the expected result and the result obtained by the model. From the loss function, we get the gradients that are used to update the weights. For this model, "CrossEntropyLoss" was used, which is most often used in the case of

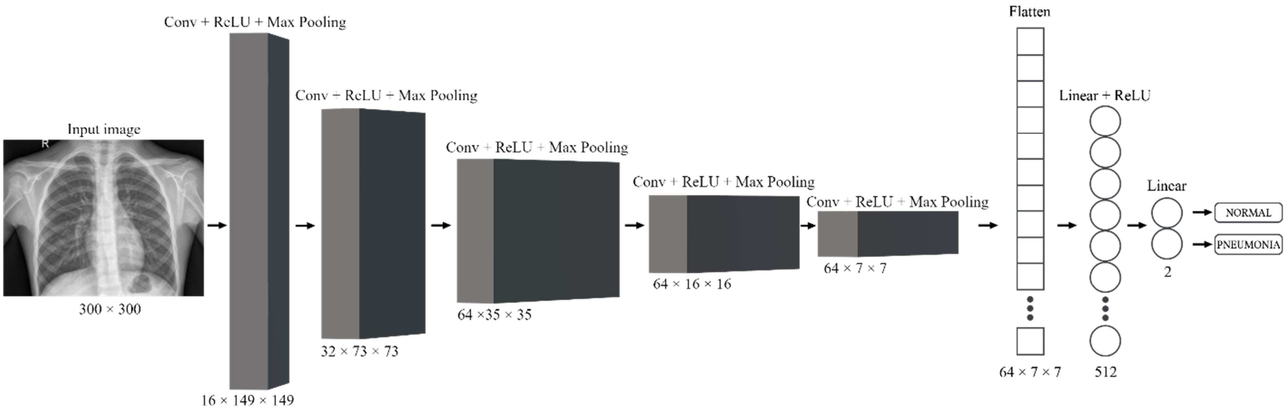

Fig. 6. The neural network architecture.

classification problems and is determined by the formula:

$$CrossEntropyLoss(Y\_predicted, Y) = -\sum Y_i \cdot \log(Y\_predicted_i),$$

where $Y\_predicted$ is the value predicted by the model, Y is the true value. In PyTorch, nn.CrossEntropyLoss immediately includes nn.LogSoftmax, which is used to classify several classes, resulting in probabilities for each class that add up to 1.

The "Adam (Adaptive Moment Estimation)" algorithm has been used as a gradient descent optimizer, which will accept the parameters of our model, as well as the learning rate. This method requires less memory and is efficient. The Adam (Adaptive Moment Estimation) optimizer includes a combination of two gradient descent methodologies: Momentum, which is used to speed up the gradient descent algorithm by taking into account the "exponentially weighted average" of the gradients, allowing the algorithm to converge to minima faster, and "Root Mean Square Propagation (RMSP)", which is an adaptive learning algorithm and uses an "exponential moving average". Adam inherits the positive properties of the above two methods and uses them to provide a more optimized gradient descent.

5. The constructed neural network training and evaluation

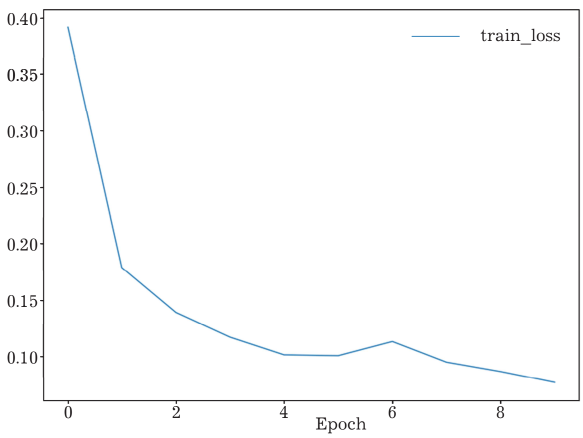

Fig. 7. The error graph.

Ten epochs have been set for training the neural network; in each epoch all the data of the training set passes through the network. Propagation of signals in the forward direction was implemented to obtain the loss function. After that, backpropagation of errors was implemented to update the weight coefficients. In Figure 7, a graph of the error is presented, which shows that the error is getting smaller with each epoch. At the beginning of training, the error was almost 0.4, and at the end it was less than 0.1 (Figure 7).

As a result of training, the accuracy of 83.8% has been achieved.

6. The neural network testing on third-party images

The proposed model for the classification of X-ray images of the lungs has been used on extraneous images. To do this, a transform_image function was implemented to transform the input images in the same way as the training image, a get_prediction function to obtain a classification prediction, and a predict function to actually output the image and the prediction for it. As a result, any X-ray image can be downloaded, and after that get a result that indicates whether the image shows healthy lungs or lungs affected by pneumonia.

To test the network on extraneous images, three images with lungs affected by pneumonia, as well as one image of healthy lungs, have been uploaded [19]. In this case, all images were classified correctly (Figure 8).

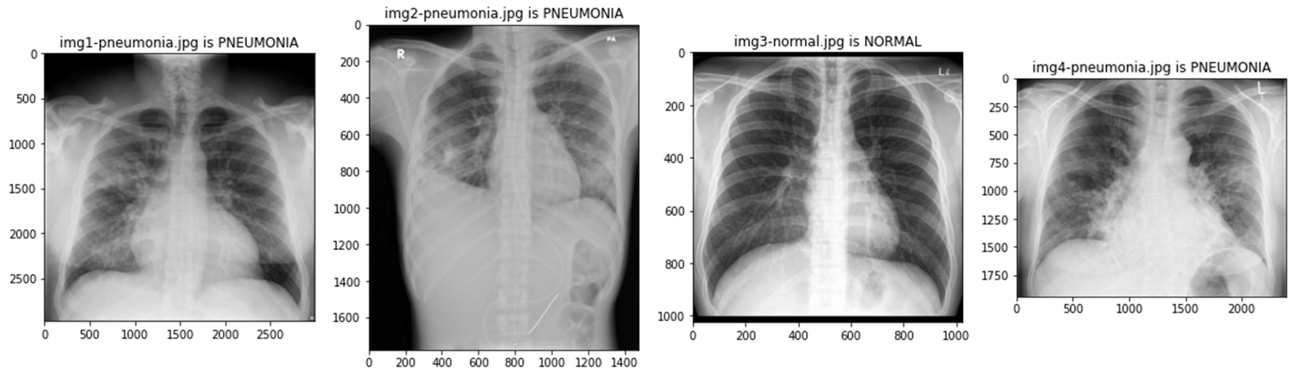

Fig. 8. Testing the work of the model on third-party images.

7. Conclusions

Doctors often face the task of quickly analyzing the X-ray images for the presence of certain injuries. In this case, machine learning methods, namely computer vision, can help in the preliminary analysis. This will help classify the most difficult cases, which will reduce the burden on the healthcare system and provide a more efficient diagnostic and therapeutic process for radiologists and other doctors.

In a way computer vision techniques can analyze images of digits or other objects and classify them, they can work similarly with X-ray images. For the classification of images, including medical ones, it is advisable to use a convolutional neural network, since such a network can recognize patterns present in images, as well as store spatial information about them.

In this work, the existing neural networks for the analysis of medical images were analyzed. A convolutional neural network consisting of 5 convolutional layers and 2 linear layers has been built. After training the network, an accuracy of 83.8% was achieved on the test data set. These results are partially satisfactory because this model will classify incorrectly more than 15% of cases, which is unacceptable when working in the field of health care. Such results may be related to the fact that the data set is quite small, as well as the X-ray images are quite uniform and the model is quickly retrained. Data sets with more images should be used for better results.

[1] Chemlal Y., Azouazi M. Implementing quality assurance practices in teaching machine learning in higher education. Mathematical Modeling and Computing. **10** (3), 660–667 (2023).

[2] Bellaj K., Benmir M., Boujen S. Enhancing image inpainting through image decomposition and deep neural networks. Mathematical Modeling and Computing. **10** (3), 720–732 (2023).

[3] Krizhevsky A., Sutskever I., Hinton G. E. ImageNet classification with deep convolutional neural networks. Communications of the ACM. **60** (6), 84–90 (2017).

[4] Liu P., Lu L., Zhang J., Huo T., Liu S., Ye Z. Application of Artificial Intelligence in Medicine: An Overview. Current Medical Science. **41** (60), 1105–1115 (2021).

[5] COVID-19 Data Explorer – Our World in Data. https://ourworldindata.org/explorers/coronavirus-data-explorer.

[6] On the approval of clinical protocols for the provision of medical care in the specialty "Pulmonology": Order of the Ministry of Health of Ukraine from 19.03.2007 No 128. https://zakon.rada.gov.ua/rada/show/v0128282-07.

[7] Bursov A. I. Application of artificial intelligence in medical data analysis. Almanac of Clinical Medicine. **47** (7), 630–633 (2019).

[8] Van Ginneken B. Fifty years of computer analysis in chest imaging: rule-based, machine learning, deep learning. Radiological Physics and Technology. **10** (1), 23–32 (2017).

[9] Yadav S. Brief Intro to Medical Image Analysis and Deep Learning. https://medium.com/@saurabh.yadav919/brief-intro-of-medical-image-analysis-and-deep-learning-810df940d2f7.

[10] Topol E. J. High-performance medicine: the convergence of human and artificial intelligence. Nature Medicine. **25** (1), 44–56 (2019).

[11] Elgendi M., Nasir M. U., Tang Q., Fletcher R. R., Howard N., Menon C., Ward R., Parker W., Nicolaou S. The Performance of Deep Neural Networks in Differentiating Chest X-Rays of COVID-19 Patients From Other Bacterial and Viral Pneumonias. Frontiers in Medicine. **7**, 550 (2020).

[12] Almezhghwi K., Serte S., Al-Turjman F. Convolutional neural networks for the classification of chest X-rays in the IoT era. Multimedia Tools and Applications. **80** (19), 29051–29065 (2021).

[13] Tang Y.-X., Tang Y.-B., Peng Y., Yan K., Bagheri M., Redd B. A., Brandon C. J., Lu Z., Han M., Xiao J., Summers R. M. Automated abnormality classification of chest radiographs using deep convolutional neural networks. npj Digital Medicine. **3** (1), 70 (2020).

[14] Pasa F., Golkov V., Pfeiffer F., Cremers D., Pfeiffer D. Efficient Deep Network Architectures for Fast Chest X-Ray Tuberculosis Screening and Visualization. Scientific Reports. **9** (1), 6268 (2019).

[15] Maity A., Nair R. T., Chandra A. Image Pre-processing techniques comparison: COVID-19 detection through Chest X-Rays via Deep Learning. International Journal of Scientific Research in Science and Technology. **7** (6), 113–123 (2020).

[16] Patel O., Maravi P. S. Y., Sharma S. A Comparative Study of Histogram Equalization Based Image Enhancement Techniques for Brightness Preservation and Contrast Enhancement. Signal & Image Processing: An International Journal. **4** (5), 11–25 (2013).

[17] Gieiczyk A., Marciniak A., Tarczewska M., Lutowski Z. Pre-processing methods in chest X-ray image classification. PLOS ONE. **17** (4), e0265949 (2022).

[18] Chest X-Ray Images (Pneumonia). https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia.

[19] Hacking C., Luong D. Pneumonia. https://radiopaedia.org/articles/pneumonia.

Машинне навчання для виявлення уражень легень, які спричинені певними захворюваннями

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Стаття присвячена використанню нейронних мереж для аналізу медичних зображень, а саме: Х-променевих зображень. Здійснено огляд нейронних мереж, які використовуються для аналізу медичних зображень. Така нейромережа була реалізована та протестована на сторонніх зображеннях.

Ключові слова: *класифікація зображень; згорткові нейронні мережі; глибоке навчання; Х-променева радіографія грудної клітки.*