Methods for Medical Images Contrast Measuring and Enhancement to Improve the Accuracy of Pathology Detection

Alexander Kutsenko
dept. of System Analysis and Information-Analytical Technologies
National Technical University "KhPI"
Kharkiv, Ukraine
kuzenko@i.ua

Yury Megel
dept. of Cybernetics and Information Technologies
State Biotechnology University
Kharkiv, Ukraine
megelye@gmail.com

Sergii Kovalenko
dept. of System Analysis and Information-Analytical Technologies
National Technical University "KhPI"
Kharkiv, Ukraine
adbc@ukr.net

Svitlana Kovalenko
dept. of Software Engineering and Management Intelligent Technologies
National Technical University "KhPI"
Kharkiv, Ukraine
svetkovalenko@gmail.com

Daniil Pelikh
dept. of System Analysis and Information-Analytical Technologies
National Technical University "KhPI"
Kharkiv, Ukraine
daniil.pelikh@cs.khpi.edu.ua

Antonina Rybalka
dept. of Physics
Kharkiv National University of Radio Electronics
Kharkiv, Ukraine
antonina.rybalka@nure.ua

***Abstract*—the article describes the process of developing software for enhancing the contrast of radiographs and comparing the impact of these methods on the accuracy of determining the pathology. The paper provides an overview and analysis of the use of artificial neural networks in various fields of medicine. This research describes and implements contrast enhancement methods, such as: image contrast enhancement method using entropy, image contrast enhancement method using standard deviations of local neighborhood element brightness values, local contrast non-linear transformation method, image contrast enhancement method using statistical determination of local contrasts, method using the standard deviation of the intensities of the elements of the local neighborhood of the image. The results of the methods were compared using data analysis. As a result, software was developed to enhance image contrast and train the neural network of the VGG16 architecture.**

Keywords—medicine, diagnostics, digital image processing, radiograph, contrast, neural network

I. INTRODUCTION

The rapid development of new technologies and tools for diagnostic imaging is due to the modern needs of mankind in the emergence of new systems and methods that expand the possibilities of clinical monitoring and improve the quality of life of people. A significant increase in the technical level of development of modern non-invasive diagnostic systems due to the improvement of hardware implementation and production technologies makes diagnostic imaging systems indispensable in everyday clinical practice. At the same time, along with the progress of tools, computer methods for processing graphic information are now beginning to play a very significant role. Modern methods of computer processing of biomedical images provide image enhancement for better visual perception by a diagnostician, efficient image compression for reliable storage and processing by machine learning methods.

Among the current areas of biomedical research, the most promising are the development and implementation of intelligent systems for diagnosing and predicting modern human diseases. Nowadays, various mathematical methods and algorithms are effectively used to solve problems of medical diagnostics and forecasting. Among those that deserve more attention in recent years are systems based on the mathematical apparatus of artificial neural networks.

The introduction of artificial neural network diagnostic models into clinical practice can provide effective assistance in prescribing medications, help improve the quality and accuracy of disease diagnosis, and reduce the time for patient examination. It should also be noted that artificial neural networks can be used as mathematical models of the subject area. By changing the input parameters of the neural network model, and observing the behavior of the output signals, it is possible to study the subject area, identify and investigate medical patterns extracted by the artificial neural network during training. The information obtained will expand theoretical knowledge in various fields of medicine.

Fig. 1 shows a typical workflow or pipeline for finding a solution using artificial intelligence.

The use of deep learning in medicine is actively developing due to the large number of sets of labeled images, increased computing power and the emergence of cloud data storage. Neural networks affect the state of medicine on three levels: help doctors quickly and accurately interpret images; reduce the number of medical errors; help patients to monitor their condition by self-analyzing data using sensors.

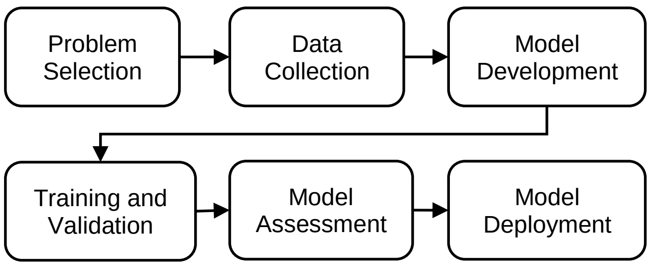

Fig. 1. Scheme for finding a solution using artificial networks

In the areas of modern medicine, a new area of processing and analysis of visual data is actively developing – radiomics. It is a computer technology that allows deeper analysis of medical images such as computed tomography (CT), magnetic resonance imaging (MRI), chest

X-Ray (CXR). This approach allows extracting quantitative textural features from images and isolating biological markers to describe pathology, which provides a personalized approach to diagnosis and treatment. Spectral decomposition and neural networks for processing and analyzing visual data are a priority approach to solving such applied problems.

At the same time, in the process of pattern recognition in images when making decisions, medical specialists face a number of problems: incomplete and inaccurate initial information; large variability in attributes and small sample sizes; limited decision time for conclusions [1]. These factors often lead to misdiagnosis. In order to improve the efficiency and quality of experimental information processing, it is necessary to improve and modify methods for analyzing visual data, in order to improve the quality of medical images and the accuracy of object recognition.

II. Review of the Use of Artificial Neural Networks in Medicine

Object detection can be implemented using a traditional approach based on image processing [2, 3] and deep learning networks [1, 4]. Each of the approaches has its pros and cons.

The image processing approach does not require a training dataset and is unsupervised in nature. This is a significant difference from deep learning networks, which is an example of supervised learning and requires a huge amount of labeled and annotated data.

Thus, the advantages of the traditional approach are the aforementioned absence of the need for a set of annotated data for training and small computing resources of the computer system. The disadvantages include the difficulty of detecting objects against a heterogeneous background, identifying part of the objects, as well as the difficulty in identifying objects in the presence of shadows and interference.

The advantages of using deep learning networks include a significant increase in the detection of overlapping objects, the recognition of complex scenes in low light. However, this approach has significant drawbacks. The first of them is the significant computing power of computers, and for large tasks the need for a graphics processor (GPU). The second significant drawback is the need for data to train the network. For the task of recognizing many objects in an image for training, you need to have a huge amount of annotated data, which in itself is a rather difficult task.

Some sources [4–5] claim that the disadvantages of the neural network approach can be overcome by using cloud services, and for training use annotated datasets that are in the public domain.

Programs using neural networks in computer diagnostics generate the main flow of computational content in medical imaging. Their relevance and range of use are all-encompassing for medical problems because of follows: neural networks have the nature of adaptive learning based on input information and, using an appropriate learning algorithm, can improve themselves according to the diversity and change of input content; neural networks are able to optimize the relationship between inputs and outputs through distributed computing, learning and processing, which leads to reliable solutions, the required specifications; medical diagnosis is based on visual examination and medical imaging is the most important diagnostic tool.

Artificial neural networks are effectively used in the field of cardiology [4], oncology [5], pulmonology, diagnostics of the gastrointestinal tract, diagnostics of diseases of the spine and skeletal system, blood diseases, as well as neurodegenerative disorders [6, 7], etc.

III. Research Problem Statement

The relevance of the work lies in the fact that today more than ever it is necessary to find an approach that effectively classifies pneumonia, COVID-19 and healthy chest x-ray images using deep learning. X-ray images are known to contain a lot of noise and are low-density black-and-white images. For this reason, the contrast in X-ray images obtained from some devices may be very weak. Extracting useful information from such radiographs is quite difficult.

The quality of these images can be improved using some contrast enhancement techniques. Thus, information from images can be obtained more efficiently and comfortably. This study will analyze the impact of existing imaging techniques that provide the greatest impact on improving the accuracy of pathology detection on a chest x-ray. The best method will be chosen that will allow the network to most accurately solve the classification problem. In addition, the authors developed algorithms and software designed for pathology recognition in order to increase the speed and accuracy of screening pathology and assessing the patient's condition.

Theoretical and applied research on improving algorithms related to the use of neural networks within a single computing technology for solving problems of assessing the state of an object (detection and classification of pathologies and neoplasms) on medical images (CXR-scanning, CT and MRI- images) are also relevant.

IV. Raster Image Enhancement Techniques

By image enhancement methods, we mean the implementation of transformations on the original image, leading to a result that is more suitable from the point of view of a particular application. Visual evaluation of image quality is a highly subjective process. In the case when the purpose of image processing is further use in machine perception systems, the criterion for the effectiveness of processing the original image is to obtain more accurate results of machine recognition [8].

A variety of image enhancement approaches can be divided into 2 categories: spatial domain processing techniques and frequency domain processing techniques. The term spatial domain refers to the area of an image, and this category encompasses approaches based on direct manipulation of image pixels.

Spatial methods are procedures that operate directly on pixel values and are described by the equation:

$$g(x, y) = T[f(x, y)], \quad (1)$$

where $f(x, y)$ is an input image, $g(x, y)$ is an processed image, T is an operator over f, defined in some neighborhood of the point (x, y). The neighborhood of a point is a square or rectangular area that is a subset of the image and is centered on the given point [3].

A. Contrast enhancement using image entropy

For this, the method of adaptive transformation of local contrasts is used, in which the parameter characterizing the variable neighborhood is used as an analogue of entropy.

To improve the efficiency of the described method, it is proposed to use the classical probabilistic approach to the definition of entropy.

$$P(i,j) = \frac{H(L(i,j))}{n \cdot m}, \tag{2}$$

where $H(L(i,j))$ is a histogram value for the element with luminance values $L(i,j)$; n, m is a dimension of variable neighborhood W.

In addition, an expression for the local contrast transformation is proposed:

$$C'(i,j) = C(i,j)^{\alpha_{\min} + (\alpha_{\max} - \alpha_{\min})\left(\frac{\varepsilon(i,j) - \varepsilon_{\min}}{\varepsilon_{\max} - \varepsilon_{\min}}\right)^{s}}, \tag{3}$$

where $\varepsilon_{\max}$, $\varepsilon_{\min}$ are the maximum and minimum entropy value of the variable neighborhood W; $s > 1$ is a parameter of nonlinear contrast enhancement.

B. Contrast enhancement using the mean deviation of the brightness values of the neighborhood elements

The method using image entropy does not sufficiently take into account adaptation to local features of the image. To increase the efficiency, it is proposed to additionally evaluate the local neighborhoods of the image, taking into account the root-mean-square deviations in relation to the brightness of the central element and, on this basis, form the function of the nonlinear transformation of the local contrasts of the brightness of the image elements. We define the value of the exponent as follows:

$$\alpha = \alpha_{\max} - k\frac{\bar{L}}{\sigma(i,j)}, \tag{4}$$

where k is a normalizing coefficient, $0 < k < 1$, $\sigma(i,j)$ – is the standard deviation of the brightness values of the image elements in the changing neighborhood, $\bar{L}$ is the arithmetic mean of the brightness of the original image:

$$\bar{L} = \frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M} L(i,j), \tag{5}$$

where N, M are image sizes.

Therefore, using the standard deviation $\sigma(i,j)$ as a quantitative estimate of the smoothness of the image in a changing neighborhood, we obtain a direct dependence of the degree α on $\sigma(i,j)$. This allows, generally, implementing an adaptive enhancement of local contrasts during their power-law transformations.

C. Contrast enhancement using non-linear transformations

For a nonlinear local contrast transformation, the following expression is used:

$$C'(i,j) = \begin{cases} B_0 + \left(\frac{R}{2} - A_0\right)\left(\frac{C(i,j) - C_{\min}}{\hat{C} - C_{\min}}\right)^{\alpha}, \text{for } C(i,j) \le \hat{C}, \\ R - A_0 - \left(\frac{R}{2} - A_0\right)\left(\frac{C_{\max} - C(i,j)}{C_{\max} - \hat{C}}\right)^{\alpha}, \\ \text{for } C(i,j) > \hat{C}, \end{cases} \tag{6}$$

where $C(i,j)$ is the local contrast value of the source image element with coordinates (i,j); $C'(i,j)$ enhanced value of the local contrast of the image element with coordinates; R is the maximum possible value of local contrast; $C_{\min}$, $C_{\max}$ are the maximum and minimum values of the local contrast of the original image; $\hat{C}$ is the estimation of the mathematical expectation of local contrast values (for example, the arithmetic mean of local contrasts of image elements; A_0, B_0 are constant bias coefficients; α is an exponent.

D. Contrast enhancement using statistical methods

The essence of the local contrast enhancement method is to determine the numerical value of the local contrast for a certain image element, its non-linear amplification and restoration of the same image element with changed brightness, which provides local contrast enhancement compared to the original image.

Restoring an image by defining a new brightness value of an element $L^*(i,j)$ with coordinates (i,j):

$$L^*(i,j) = \bar{L}(i,j) + \left(\frac{C^*(i,j)nm}{1 - C^*(i,j)} - \sum_{\forall i,j \notin W_2 - W_1}(\bar{L}(i,j) - L(i,j))^2 H(L(i,j))\right)^{0.5}. \tag{7}$$

The proposed method uses statistical determination of local contrasts, due to which such texture characteristics as uniformity, roughness, and graininess are taken into account. Therefore, this method is recommended for processing images that contain small details.

E. Increasing the contrast using the standard root mean square deviation of the intensities of elements of the local neighborhood of the image

Image quality in local areas can be improved using pixel intensity parameters such as average intensity value and intensity variation [9] (or standard deviation of intensities of local image neighborhood elements).

A typical local transformation based on these parameters maps the intensity of the original image into the intensity of the new image by performing the following operation on the location of each pixel:

$$L^*(i,j) = k\frac{\bar{L}}{\sigma(i,j)}(L(i,j) - \bar{L}_{\text{local}}(i,j)) + \bar{L}_{\text{local}}(i,j), \tag{8}$$

where $\bar{L}$ is the average value of the intensity of elements in the image, $\sigma(i,j)$ the standard deviation of the intensities of the elements of the local neighborhood of the image at the point, $\bar{L}_{\text{local}}$ is the average value of the intensity for the neighborhood centered at the point (i, j), k is some constant for which $0 < k < 1$.

V. Description of the Used Data Set

In this research we used a data set presented and prepared by the Clinical Center of the US National Institutes of Health (NIH Clinical Center). The data set is referred to as the NIH Chest X-rays Dataset. The key selection criterion was the number of images contained in the set, since one of the features of deep learning methods is the need for the largest amount of input data.

The selected dataset is freely available and contains over 112 000 images [10]. Images are in PNG format with 8-bit color depth. Each image has a resolution of 1024×1024 pixels, which requires some pre-processing (for example, size reduction, rejection of photo quality that cannot be improved) to increase the speed of the neural network and algorithms to enhance contrast. After analyzing the content of the data, the ratio of images without pathologies (about 60% of data) to the number of images containing any pathology (about 40% of data) was established.

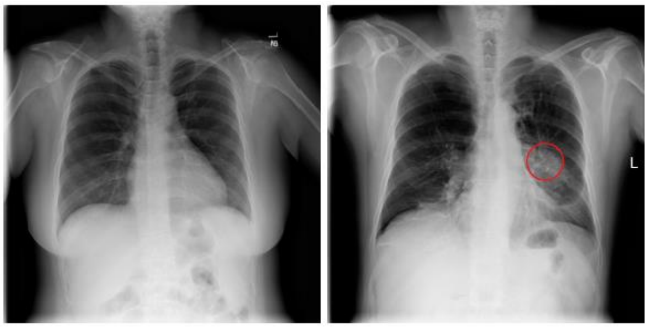

Fig. 2. An example of a radiograph without pathology (left) and with pathology (right), highlighted by a red circle from the selected data set

Due to the fact that the purpose of this work is, first of all, to analyze the effectiveness of contrast enhancement methods, for the classification itself, a model was chosen that meets the minimum requirements: a simple structure and short training time [11]. Based on these requirements, a standard convolutional neural network model based on the VGG16 architecture was chosen.

Convolutional layers apply a convolution operation to the input, passing the result to the next layer. Convolution simulates the response of a single neuron to a visual stimulus.

The software implementation of artificial neural network training was performed in the Python programming language using the Anaconda distribution, using open software libraries for machine learning TensorFlow with Keras API. Keras [12] allows you to use distributed training of deep learning models on clusters of graphic and tensor processors mainly in connection with CUDA.

An instance of the VGG16 neural network was used with weights previously obtained on ImageNet, but without a fully connected layer. After obtaining the weights, a fully connected layer consisting of POOL $\rightarrow$ FC = SOFTMAX layers was added and placed on top of VGG16. CONV layers were forbidden to learn, so that only the added connected layer will learn.

At first, the initial training frequency, the number of training epochs, and the batch size were set. The first hyperparameter is responsible for the number of weights updated during training, called step size or training speed.

In particular, the learning rate is a tunable hyperparameter that is used when training neural networks and has a small positive value, usually in the range (0, 1). The learning rate determines how quickly the model adapts to the task. Too high learning rate can cause the model to converge too quickly on a sub-optimal solution, while too low learning rate can cause the process to get stuck. For the task of determining the presence of pathology, a learning rate value of 0.001 was chosen.

In the terminology of neural networks, an epoch is one iteration in the training process (obtaining the initial values and updating the weights of all training instances). For this research we chose the number of epochs to be 25. The batch size (the number of training examples used in one iteration) was chosen to be 10, i.e. this is a mini-batch mode, given that the number of samples per contrast enhancement method is 100.

From the very beginning, radiographs were divided into two folders with appropriate names (covid and normal), the names of these folders are simultaneously used as class labels. Moreover, not only pictures of perfectly healthy people were placed in the normal folder, but also pictures with diseases other than Covid-19 (for example, minor pulmonary edema or a very mild form of bacteriological pneumonia). 50 x-rays of people without the coronavirus and 50 x-rays of people with the coronavirus were used [13].

As a result, we used 4 pairs of such folders: original images; images processed by the contrast enhancement method using the average deviation of the brightness values of the neighborhood elements; images processed by the contrast enhancement method using the moments of the histogram of the image element intensities; images processed by the contrast enhancement method using the standard deviation of the intensities of the elements of the local neighborhood of the image.

For the neural network application, the images were scaled down to 224×224 pixels, and the pixel intensities were scaled to be in the range 0 to 1. Then, for training and testing, the set of radiographs was split as follows: 80% for training and 20% for testing.

The neural network is trained using the Adam optimizer, which uses learning rate decay. Given the fact that the task is to detect whether there are pathologies on this X-ray or not, the loss function of binary cross entropy was used, and not categorical cross entropy. A confusion matrix was calculated to analyze the learning results. This matrix was used to determine accuracy, sensitivity, and specificity.

VI. Measurements and Comparisons

Among the methods for improving the contrast for image preprocessing, the method using image entropy, the method using the average deviation of the brightness of the neighborhood elements and the method of nonlinear stretching of local contrasts, the method using the moments of the histogram of the intensities of the image elements, the method using the standard deviation of the intensities of the elements of the local neighborhood Images (fig. 3). But only those methods that will have a significant impact on the image histogram will be used to train the neural network [14, 15].

The brightness distribution almost did not change after processing by the method using image entropy. The increase in the number of light pixels and the decrease in the number of dark pixels are barely noticeable. Therefore, this method was not used when training the neural network.

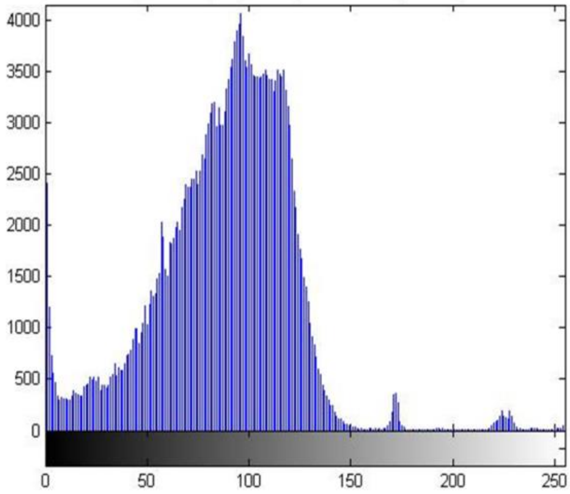

Fig. 3. Contrast enhancement using image entropy

The method using the average deviation of the brightness of the elements of the neighborhood gives a much better result even by visual assessment and the histogram of the resulting image. This method increases the contrast and detail of the image, and allows you to evaluate the boundaries of transitions from one brightness level to another. Next, the influence of this method on the accuracy of detecting pathologies by radiographs will be tested.

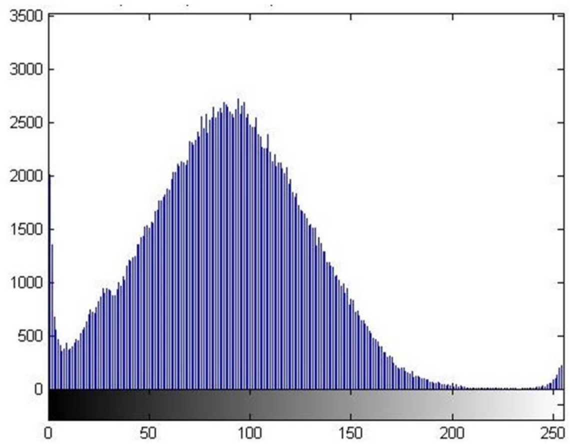

Fig. 4. Histogram of the image after processing, using the average deviation of the brightness of the neighborhood elements

The result of the algorithm for contrast enhancement using statistical methods made the histogram of the resulting image smoother, and a more uniform distribution of brightness became noticeable.

The result of the algorithm for contrast enhancement using the standard deviation of the intensities of the elements of the local neighborhood of the image is also suitable for further comparison with methods that can have a significant impact on training the neural network and improving classification accuracy.

Thus, among the contrast enhancement methods to study their influence on neural network training, the method of using the average deviation of the brightness values of the elements, the method for increasing the contrast using statistical methods, and the method for increasing the contrast using the standard deviation of the intensities of the elements of the local edge of the image were chosen.

Let's consider the work of these methods on practical examples. Such texture characteristics as uniformity, roughness and graininess are most fully described by statistical methods. One of the more common ways to describe texture is to use the moments of the histogram of image element intensities.

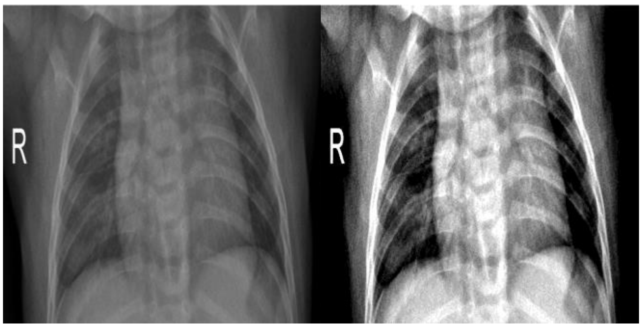

Fig. 5. Photo before (left) and after (right) applying the contrast enhancement method using the moments of the histogram of image element intensities

The histogram of the resulting image in fig. 2 is smoother, and the brightness distribution is noticeably more even.

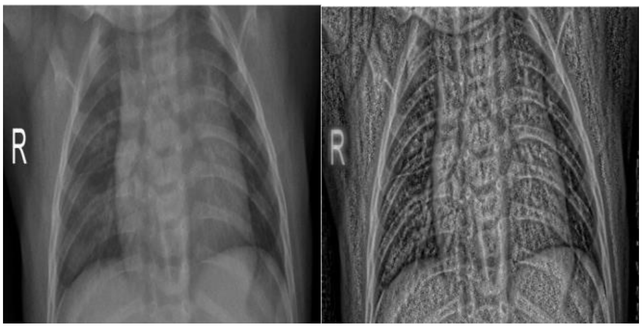

Fig. 6. Photo before (left) and after processing (right) by a method that uses the standard deviation of the intensities of the elements of the local image neighborhood

The histogram of the resulting image in fig. 4 is smoother than the histogram of the original image.

First, a set of raw images was set to the input of the neural network. The result of training is presented in tab. 1.

TABLE I. RESULTS FOR THE MODEL TRAINED ON THE RAW IMAGE SET

	precision	**recall**	**f1-score**	**support**
covid	0.83	1.00	0.91	10
normal	1.00	0.80	0.89	10
accuracy			0.90	20
macro avg	0.92	0.90	0.90	20
weighted avg	0.92	0.90	0.90	20
acc: 0.9000 sensitivity: 1.0000 specificity: 0.8000				

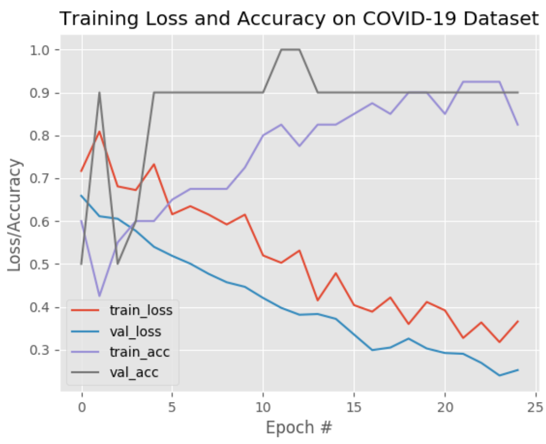

Fig. 7. Model accuracy and loss function according to epochs

Further, radiographs that were processed by the method of contrast enhancement using the moments of the image elements intensities histogram (tab. 2).

From tab. 2, it can be seen that the results have changed, which indicates that this method has a certain influence on the determination of the radiograph class. All the diagnoses turned out to be correct.

TABLE II. RESULTS FOR MODEL TRAINED ON CONTRAST ENHANCEMENT USING THE MOMENTS OF THE IMAGE ELEMENTS INTENSITIES HISTOGRAM

	precision	**recall**	**f1-score**	**support**
covid	1.00	1.00	1.00	10
normal	1.00	1.00	1.00	10
accuracy			1.00	20
macro avg	1.00	1.00	1.00	20
weighted avg	1.00	1.00	1.00	20
acc: 1.0000 sensitivity: 1.0000 specificity: 1.0000				

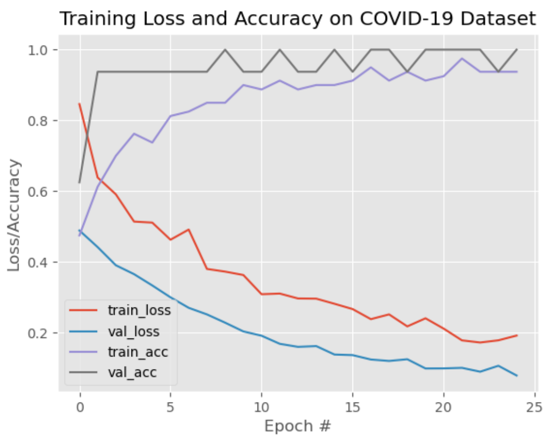

Fig. 8. Model accuracy and loss function according to epoch number

From fig. 8, it can be seen that overfitting did not occur, and the number of errors between epochs 20 and 25 decreased even more compared to the previous method. The era accuracy on the test set also slightly increased, often approaching 1.

VII. CONCLUSIONS

The contrast enhancement method using pixel intensity histogram moments (F-score = 1) was the best aid in training the model. The second was the method using the average deviation of the brightness values of the neighborhood elements (F-measure = 0.95). The third was the method using the standard deviation of the intensities of the elements of the local neighborhood of the image (F-score = 0.9), that is, this method had no effect on the quality of training (F-score at the beginning on the raw sample reached 0.9).

It should be noted separately that the result of most studies using neural networks more often and to a greater extent depends on the quality of the used dataset. But if we are talking about research related to image analysis, it is the methods used for image preprocessing that have a significant impact on the accuracy of solving the classification problem.

REFERENCES

[1] R. M. Rangayyan, Biomedical Image Analysis, CRC Press, Boca Raton, 2005. – 1306 p.

[2] A. S. Kutsenko, Y. Y. Megel, S. V. Kovalenko, S. M. Kovalenko, Z. Omiotek, and U. Zhunissova "An approach to quality evaluation of embryos based on their geometrical parameters", Proc. SPIE 11176, Photonics Applications in Astronomy, Communications, Industry, and High-Energy Physics Experiments 2019, 111762G (6 November 2019). doi: 10.1117/12.2536420.

[3] Y. Megel, I. Kalimanova, A. Rybalka, S. Kovalenko, and S. Kovalenko, "Automation of measurement of objects geometrical parameters", Proceedings of International Scientific Symposium "Metrology and Metrology Assurance", 2017, pp. 225-259.

[4] H. Bihri et al. An Artificial Neural Network-Based System to Predict Cardiovascular Disease //The International Conference on Information, Communication & Cybersecurity. – Springer, Cham, 2021. – С. 393-402.

[5] P. S. Maclin, J. Dempsey, How to Improve a Neural Network for Early Detection of Hepatic Cancer // Cancer Lett. 1994. Vol. 77, № 2-3. P. 95–101.

[6] D. Mantzaris, M. Vrizas, S. Trougkakos, E. Priska, K. Vadikolias, Artificial Neural Networks for Estimation of Dementias Types // Artif. Intell. Appl. 2014. Vol. 1, № 1. P. 74–82.

[7] M. Quintana, J. Guàrdia, G. Sánchez-Benavides, M. Aguilar, J. L. Molinuevo, A. Robles, M. S. Barquero, C. Antúnez, C. Martínez-Parra, A. Frank-García, M. Fernández, R. Blesa, J. Peña-Casanova, Neuronorma Study Team. Using Artificial Neural Networks in Clinical Neuropsychology: High Performance in Mild Cognitive Impairment and Alzheimer's Disease // J. Clin. Exp. Neuropsychol. 2012. Vol. 34, № 2. P. 195–208.

[8] M. Nixon, A. Aguado, Feature extraction and image processing for computer vision. – Academic Press, 2019.

[9] C. Wang, Y. Xi, "Convolutional neural network for image classification", Johns Hopkins University Baltimore, MD, 1997. Т. 21218.

[10] National Institutes Of Health Chest X-Ray (NIH Chest X-rays) – 2018. – Access mode: https://www.kaggle.com/nih-chest-xrays/data.

[11] Y. Megel, A. Kutsenko, I. Blagov, S. Kovalenko, S. Kovalenko, M. Malko and A. Rybalka "Information System for Automating Processes of Biological Objects Detection, Recognition, and Measurement," 2021 XXXI International Scientific Symposium Metrology and Metrology Assurance (MMA), 2021, Sozopol, Bulgaria, 2021, pp. 1-6. doi: 10.1109/MMA52675.2021.9610832.

[12] W. Burger, and M. J. Burge, "Digital image processing: an algorithmic introduction using Java", Springer, 2016, 811p.

[13] Joseph V. Hajnal, L. G. Derek, Hill Medical Image Registration, CRC Press, Boca Raton, 2001. – 392 p.

[14] S. van der Walt, J. L. Schönberger, J. Nunez-Iglesias, F. Boulogne, J. D. Warner, N. Yager, E. Gouillart, T. Yu, and the scikit-image contributors. 2014. "scikit-image: image processing in Python", PeerJ 2, :e453, 2014, doi:10.7717/peerj.453

[15] L. Eastwood, and J. Smith. "Determining the Size of Finisher Pigs, Replacement Gilts and Sows", Ontario Ministry of Agriculture, Food and Rural Affairs, 2020, 7 p.