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Detection of chest pathologies using autocorrelation functions

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ABSTRACT

An important feature of image analysis is texture, seen in all images, from aerial and satellite images to microscopic images in biomedical research. A chest X-ray is the most common and effective method for diagnosing severe lung diseases such as cancer, pneumonia, and tuberculosis. The lungs are the largest X-ray object. The correct separation of the shapes and sizes of the contours of the lungs is an important reason for diagnosis, because of which an intelligent information environment can be created. Despite the use of X-rays, to identify the diagnosis, there is a chance that the disease will not be detected. In this sense, there is a risk of development, which may be fatal. The article deals with the problems of pneumonia clustering using the autocorrelation function to obtain the most accurate result. This provides a reliable tool for diagnosing lung radiographs. Image pre-processing and data shaping play an important role in revealing a well-functioning basis of the nervous system. Therefore, images from two classes were selected for the task: healthy and with pneumonia. This paper demonstrates the applicability of the autocorrelation function for highlighting interest in lung radiographs based on the fineness of textural features and k-means extraction.

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1. INTRODUCTION

With the spread of radiation diagnostic methods, the volume of workload on radiologists has increased significantly. The constant process of digitalization in healthcare allows the use of more and more new technologies in various areas of medicine. Currently, the Government of the Republic of Kazakhstan is actively involved in the digitalization of all sectors and areas of the economy. On December 26, 2019, the Ministry of Health of the Republic of Kazakhstan presented the "State Program for the Development of Healthcare of the Republic of Kazakhstan for 2020-2025", which contains several indicators to improve the quality of life of the population, the achievement of which is planned by 2025. One of the main focuses of the program will be strengthening the health of children, adolescents, and young people through the prevention of diseases, the provision of timely assistance, and full rehabilitation taking into account the best international practice, following the approaches in the Health Strategy for 2016-2030 of UNICEF. The epidemiological situation for infectious diseases in the Republic of Kazakhstan for 2018 is stable. A decrease in the incidence of 34 infectious and parasitic diseases has been achieved.

The study aims to develop an instrumental environment for the automatic classification of radiograph images based on autocorrelation functions. With the goal, to realize the capabilities of the software being created, it was necessary to solve the following tasks: to analyze the existing methods and develop algorithmic and mathematical software for highlighting a homogeneous area with pathology in an image. For the study, the data were reviewed from [1] and verified by mathematical methods to identify pathologies, to further assess the possibility of introducing artificial intelligence into the working practice of a radiologist, as well as to optimize work with fluorograms to reduce workload and resource costs. Health-related digital data is expanding from the more obvious and traditional, such as records in a medical record, to sometimes less obvious information about our daily lives, as well as a wide range of data describing the environment in which we live. The constant process of digitalization in healthcare allows the use of more and more new technologies in various areas of medicine [2]. With the spread of radiation diagnostic methods, the volume of workload on radiologists has increased significantly. In 2019, it was estimated that the average radiologist must interpret a fluorogram, radiograph, or one computed tomography (CT) or magnetic resonance imaging (MRI) image every 3–4 seconds during an 8-hour workday to meet demand. This increasing number of images requiring interpretation means that the amount of work has increased significantly. With technological advances, radiologists are processing more and more images in a single exam. Reducing the time to perform work is of great interest not only to reduce the burden on the radiologist but also to reduce resource costs, thereby improving the economic situation in the health care of the Republic of Kazakhstan [2]. Chest fluorography is one of the most commonly used X-ray methods in the world, currently available to researchers for the digitalization of pathology. Improving the quality of medical services and digitalization of the detection of infectious diseases is one of the topical issues within the framework of the State Program for the Development of the Healthcare Sector of the Republic of Kazakhstan for 2020-2025.

Two approaches to the problem of classifying chest radiographs for pneumonia diagnosis are compared in [3]. The first one is based on the use of neural networks, and the second one uses normalized compression distance. High values of classification quality metrics in both cases convincingly confirm the reliable differentiation of chest radiographs in healthy people from patients with pneumonia. The advantages of the first approach are obvious for large sets of training samples, and the second approach allows us to solve the same problem in the presence of a small number of classified images when the first approach does not work. This opens good prospects for the development of computational methods for pneumonia diagnosis, combining both approaches. In [4], a new shape-dependent feature descriptor based on Fibonacci-p patterns is proposed using a machine learning approach. Computer simulations show that the presented system improves the efficiency of differentiating coronavirus disease-19 (COVID-19), viral pneumonia, and normal conditions is efficient on small datasets and have faster inference time compared to deep learning methods with comparable performance.

Miroshnychenko *et al.* [5] considered the possibility of using digital X-ray tomosynthesis for automatic computer diagnostics of lung pathologies, including the detection of early stages of pneumonia (including those caused by COVID-19) and tuberculosis. The advantages of this method in comparison with digital radiography and computed tomography are shown. Digital tomosynthesis is considered an additional option, which is recommended to be installed on all existing basic radiographic systems with their transfer to digital technologies.

Ramnarine [6] showed advances in modern technology, which allow ordinary home computers to study the anatomical and pathological features that distinguish the healthy from the sick, with the accuracy of highly specialized, trained doctors. Computer vision artificial intelligence (AI) applications use medical imaging such as lung and chest X-rays (LCXRs) to facilitate diagnosis by providing a “second opinion” in addition to physician or radiologist interpretation. Deep learning methods such as convolutional neural networks (CNNs) can select features that distinguish between healthy and diseased states in other lung pathologies. This study aims to use this body of literature to apply image transformations that would help compensate for the lack of data on LCXR COVID-19.

Chandra *et al.* [7] shows a system of automatic computer diagnostics (CAD). However, such a system still lacks clinical acceptability and trust due to a gap in integration between patient metadata, radiologist feedback, and the CAD system. Three integration frameworks have been proposed in this article, namely direct integration (DI), rule-based integration (RBI), and weight-based integration (WBI). The proposed framework helps clinicians diagnose pneumonia and provides an end-to-end robust diagnostic system. The performance of the proposed method is evaluated using a private dataset consisting of 70 chest x-rays (CXR) (31 COVID-19, 14 other diseases, and 25 normal). The results show that the proposed WBI achieved the highest classification scores (accuracy=98.18%, F1 score=97.73%, and Matthew correlation coefficient=0.969) compared to DI and RI.

Flores *et al.* [8] used a generative adversarial network (GAN), which provides a method for training generative models for data augmentation. The synthesized images can be used to improve the reliability of automated diagnostic systems. However, GANs are difficult to train due to the unstable learning dynamics that can occur during training, such as mode collapse and vanishing gradients. This article focuses on Lipizzaner, a GAN learning system that combines spatial co-evolution with gradient-based learning that has been used to mitigate GAN learning pathologies. Lipizzaner improves productivity by taking advantage of its distributed nature and working at scale. Thus, the Lipizzaner algorithm and implementation robustness can be scaled to high-performance computing (HPC) to provide more accurate generative models. Experimental analysis shows improvement in performance by scaling up Lipizzaner GAN training.

Ortiz-Toro *et al.* [9] assesses the potential of three methods for characterizing texture images: radionics, fractal dimension, and engineered histone based on super pixels as biomarkers that have been used to train artificial intelligence (AI) models to detect pneumonia on chest x-rays. Models generated by three different AI algorithms are shown: K-nearest neighbors, support vector machines, and random forest. The results of this work confirmed the validity of the tested methods as reliable and easy-to-implement automatic means of diagnosing pneumonia.

In [10], an effective model for pneumonia recognition from computerized chest x-rays was developed and proposed. Several methods are appropriately used to extend the dataset preparation process. Therefore, it is more advantageous to manufacture a computerized indicator for predicting pneumonia using big information deep learning strategies. Among the wide range of different procedures, convolutional neural networks rank high in this prediction along with various classifiers. A convolutional brain network consisting of convolution and pooling layers and fully connected softmax layers towards the end to give the final prediction. In this paper, it is proposed to solve the problem of clustering using an autocorrelation function for the most accurate selection of diseases based on the results of X-ray image processing. As a result of the experiment, the autocorrelation function identified small homogeneous regions in X-ray images.

2. METHOD

Correlation analysis makes it possible to get an idea in practice about some properties of the image, for example, about the rate of change of intensity along the coordinates, about the length of homogeneous sections without decomposing them into harmonic components. The meaning of correlation analysis is to quantitatively measure the degree of similarity of various signals. For this, correlation functions are used, whose value characterizes the size of the main primitives, which, in turn, determines the uniformity of the texture, and which, in turn, as a result of experiments, is identified with pathology. Homogeneous areas in the images are considered to be texture areas that are related to the lung lobes. In this approach, the texture is related to the spatial size of the tone non-derivative elements of the image (the tone non-derivative element is an area of the image with certain pathological features). The value of the autocorrelation function is just the sign that characterizes the size of tone non-derivative elements of pathology. The spatial arrangement is characterized by a correlation coefficient, which is a measure of the linear dependence of the brightness of one image element on the brightness of another [11]. The autocorrelation function $R_{x,y}^{I(\alpha.\beta)}$, considered as a statistical and global measure, is computed along the horizontal and vertical axes of the analysis window I of an image according to:

$$R_{x,y}^{I(\alpha.\beta)} = \sum_{\alpha\in\Omega}\sum_{\beta\epsilon\Omega} I(x,y)I(x+\alpha,y+\beta) = FFT^{-1}([FFT[I(x,y)]FFT^{*}[I(x,y)]])$$

where $I(x,y)I(x+\alpha,y+\beta)$ is the translation of the analysis window of an image $I(x,y)$ by α and pixels along the horizontal and vertical axes respectively, defined on the plane Ω. FFT, $(.)*$, and $(.)-1$ denote respectively the fast Fourier transform, the complex conjugate, and the inverse transform [12].

Analysis of images of radiation diagnostics. Radiation diagnostics is the science of using radiation to study the structure and function of normal and pathologically altered human organs and systems to prevent and recognize diseases [13], [14]. One of the main directions of state policy in the field of healthcare is improving the quality of medical care. The relevance of the fact that modern medicine actively uses information support, digital technologies and telemedicine is due to the need to provide the population with highly qualified medical care. One of the conditions for improving the quality of medical services is the introduction of an e-health system [15]–[18]. Radiation diagnostics includes X-ray diagnostics, ultrasound diagnostics, X-ray computed tomography, radionuclide diagnostics, and magnetic resonance imaging

[19], [20]. In addition, interventional radiology adjoins it. X-ray methods of research are methods of studying organs using x-rays. The method of X-ray diagnostics is based on different permeability of tissues for X-rays [21]. Each of the X-ray methods has its advantages and disadvantages, and hence certain limits of diagnostic capabilities. But all X-ray methods are characterized by high information content, ease of implementation, accessibility, and the ability to complement each other. X-ray methods occupy one of the leading places in medical diagnostics: in more than 50% of cases, diagnosis is impossible without the use of X-ray diagnostics [22], [23]. The most commonly used X-ray diagnostic methods are radiography, fluoroscopy, and X-ray fluorography. Currently, film fluorography is increasingly being replaced by digital. Health information resources are currently being actively developed. In modern conditions of the dominance of information technologies, the target states of the industry are called “digital medicine” and “digital healthcare” [24], [25]. E-health uses modern digital technologies. Thanks to this, the treatment and diagnostic process is now moving to a new, high-tech level of development in the field of obtaining and implementing diagnostic and therapeutic information, accounting, and reporting data. Digital technologies have opened up opportunities for the remote exchange of medical information [26].

X-rays are currently the most suitable detector for fluorographic studies. The need to improve the reliability of registration and identification of defects in the structure of lung radiographs requires the elimination of factors that make it difficult to decipher the contrast and identification of the analyzed images, increasing the information content of methods, presenting images in a form that is more convenient for their identification, developing effective algorithms and programs for digital processing of X-ray images, solving problems, related to the nature of the disease. The X-ray image is characterized by the fact that the perturbations present on it are small, but, at the same time, the average description of the considered, for example, fluorogram, quite well reflects the local changes in the intensity values associated with the disease. In the case of converting an X-ray image into a digital form of representation, the resulting digital array is a stochastic distribution of radiation intensity in a given plane, and the solution of diagnostic problems, from the standpoint of statistical analysis of information, is already possible. The digital image is presented in the form of a digital matrix, these are numerical lines and columns. To display images, the digital matrix is transformed into a matrix of visible image elements-pixels. Each pixel, following the value of the digital matrix, has one of the shades of grayscale.

Application of an algorithm for the detection of pathologies in chest radiographs. The program was implemented in Python. The research work carried out on the algorithm in Figure 1 aims to determine the pathology of the database images. During the calculation, images from the database [4] were considered. During the work, the original images were processed. The selected lung region in the original image was selected for the study. The contrast has been increased as shown in Figures 2(a) and 2(b).

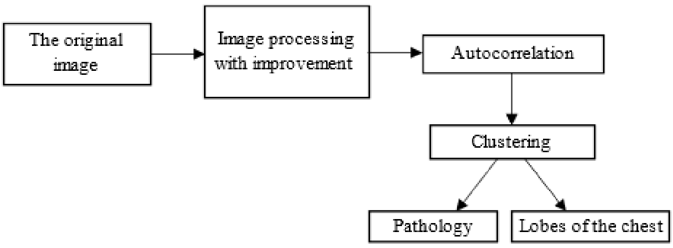
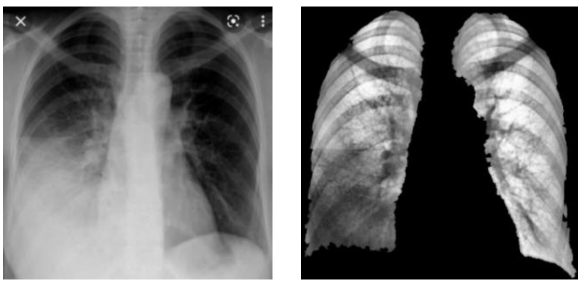


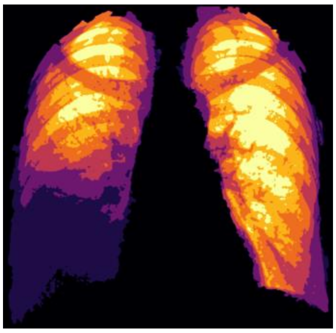
Figure 1. Stages of determining the pathology of the chest



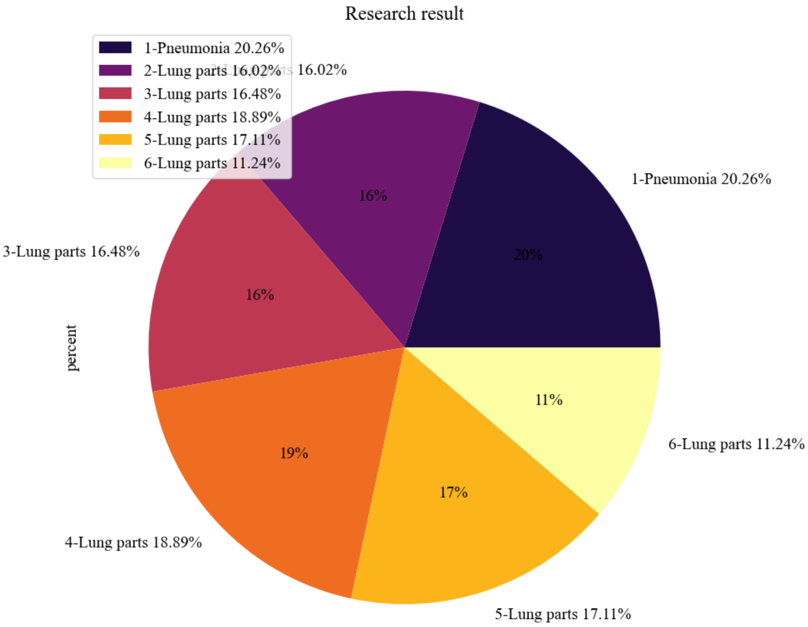
(a) (b)

Figure 2. Chest X-ray with pathology: (a) edited image of the original and (b) the contrast was enhanced after preprocessing

"Abnormal" texture areas were identified in each image; of the identified areas in Figure 3(a) and their percentage was determined in Figure 3(b). The percentage ratio was revealed through clustering. When comparing the processing data of the autocorrelation function and the data of the conclusions of radiologists, it was found that the results of the program and doctors completely coincide. The results obtained indicate the high diagnostic accuracy of the method used, as well as the possibility of using the method to automate the work of a radiologist. The deep application of the mathematical method to medical images as a matrix in digital image processing was considered.



(a)



(b)

Figure 3. The result of the experiment: (a) contrast-enhanced image clustering result, (b) percentage of lung clustering result

3. RESULTS AND DISCUSSION

During the study, 15 X-ray images from an open database were considered as the "norm". 18 X-rays-with chest pathologies. The autocorrelation function was applied to them, and the results of their values are shown in Table 1. To verify the effectiveness of the autocorrelation function method, the k-means method was considered, the graph of which is shown Figure 4. For this we used 33 X-ray images. Of these, 15 were normal and 18 with pathology.

Figure 5 shows a graph of the deviation of the normal state of the chest. The appearance of pathology as a result of the application of the autocorrelation function method as shown in Figure 5. The graph shows the values of the percentage deviation of the autocorrelation function of norm and pathology. Below is a graph of the deviation of the normal state of the chest cavity and the appearance of pathology as a result of applying the method of autocorrelation functions.

Table 1. The meaning of the results of using the autocorrelation function and the k-means method

Images title	Autocorrelation function method	K-means method
Normal-57.png	9	22
person76_bacteria_371.jpeg	21	8
Normal-61.png	15	18
person77_bacteria_377.jpeg	20	9
Normal-62.png	10	9
person80_virus_150.jpeg	25	12
Normal-64.png	17	16
person82_virus_154.jpeg	23	21
Normal-65.png	14	20
person83_virus_156.jpeg	21	20
Normal-69.png	13	21
person88_virus_163.jpeg	19	20
Normal-72.png	15	16
person88_virus_165.jpeg	30	15
Normal-74.png	13	21
person89_virus_168.jpeg	22	17
Normal-76.png	13	21
person95_virus_177.jpeg	19	17
Normal-78.png	18	17
person96_virus_178.jpeg	25	18
Normal-80.png	13	17
Normal-81.png	13	4
person97_virus_181.jpeg	22	15
person98_virus_182.jpeg	23	16
person99_virus_183.jpeg	21	17
Normal-86.png	11	24
person100_virus_184.jpeg	20	13
Normal-87.png	17	10
Normal-91.png	12	16
person102_virus_189.jpeg	19	18
person105_virus_192.jpeg	27	23
person106_virus_194.jpeg	21	8
person106_virus_195.jpeg	21	13

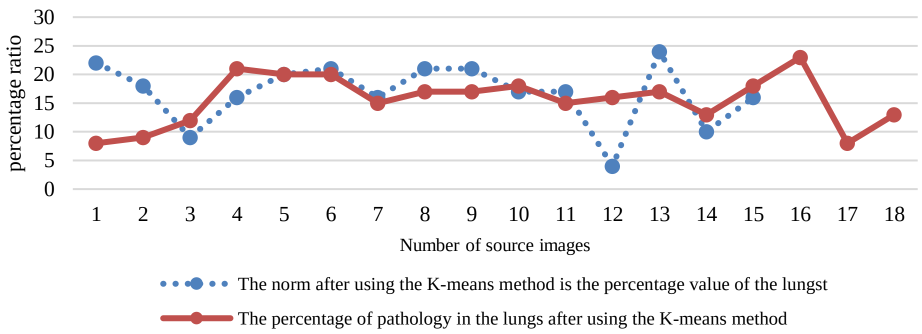


Figure 4. The result of using the K-means method

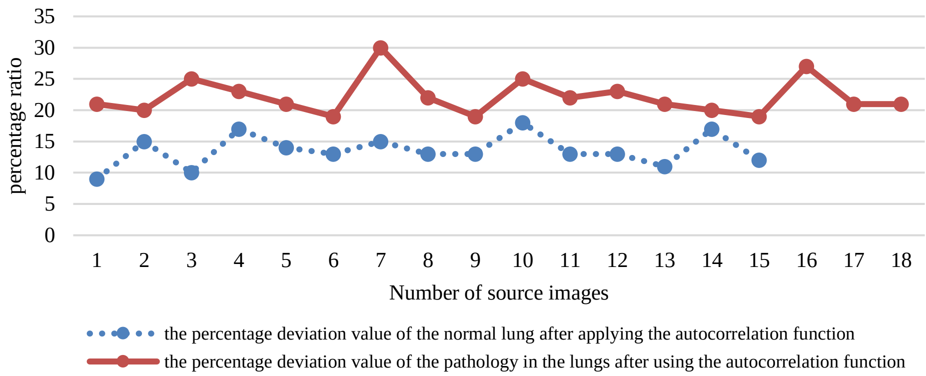


Figure 5. Graph of percentage deviation values of the autocorrelation function of norm and pathology

The Figure 5 shows that the percentage of the norm and pathology have a significant difference, which will allow a high degree of reliability to establish the boundary for determining the result of the norm and pathology. Studies have shown that this limit lies at a value of 18%. Results above this limit are highly likely to refer to images with pathology. Experiments were carried out using the k-means method to test the effectiveness of the autocorrelation function used in determining lung pathology. Based on the obtained values, the k-means method incorrectly identified 9 images as normal out of 18 pathological images, i.e., 44%, and 9 images as pathological out of 15 healthy lungs, i.e., 60%. From the result after using the autocorrelation function, 18 showed 99% accuracy for pathological images and 100% accuracy for normal images.

4. CONCLUSION

The developed algorithms for preliminary segmentation of radiographs and methods based on the use of autocorrelation functions make it possible to achieve an accuracy of recognizing pathologies of about 98%. This accuracy is determined by a small training set, therefore, in future work, it is planned to carry out differentiation on a larger number of radiographs and the neural network will be tuned. Thus, in the future, this technique will speed up the process of diagnosing diseases and reduce the proportion of repeated studies. To test the described research method, 33 fluorographic images were selected. One-half of the images had various pathologies with pneumonia, and the other half were images of healthy lungs. Radiologists play a key role in solving some current challenges of the digitalization of health care in the Republic of Kazakhstan, such as creating high-quality data sets for training, determining the clinical problem that needs to be solved, and interpreting the results. Many studies are needed for the further implementation of artificial intelligence in the practice of a radiologist, but now we can say that an automated medicine system can take over part of the workload, facilitating the work of a doctor, as well as improve the economic situation by reducing the costs of the healthcare resource base.

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