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# APPLICATION OF MATHEMATICAL METHODS AND MACHINE LEARNING ALGORITHMS FOR CLASSIFICATION OF X-RAY IMAGES

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*The relevance of the topic, in particular, if to take one of the information flows, whether it is the action of a human factor or a specific object, then it is true that special processing of the machine learning language and automatic information output significantly optimize human life. With the help of neural networks and their chest radiography is one of the most accessible radiological studies for screening and diagnosis of many lung diseases a special machine learning language is to study the flow of information about it and the same object in real time using neural networks.*

*The article describes the terminology of the problem of X-ray recognition using machine learning methods and algorithms, examines the relevance of the problem, and analyzes the current state of the problem in the field of X-ray recognition. The aspects of the problem being solved, identified during the analysis, in the form of solved problems, approaches, methods, information technologies used, tools and software solutions to the problem are noted*

*The paper is devoted to the description of a modified method of fuzzy clustering of halftone images, which at each iteration performs a dynamic transformation of the source data based on a singular decomposition with automatic selection of the most significant columns of the matrix of left singular vectors. The results of experimental studies were obtained by processing X-ray images.*

*As a result of testing a neural network model, in the output layer of which a sigmoidal activation function was used to activate neurons, and an algorithm was used as an optimization method, the best values of accuracy and completeness were obtained: accuracy – 94.2 During testing, the neural network showed an accuracy of pneumonia recognition equal to 94,27 %*

*Keywords: mathematical methods, machine learning, neural networks, pattern recognition, medical image processing, artificial intelligence*

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## 1. Introduction

Recently, methods of analyzing medical data involving deep neural networks have become increasingly developed and popular. Especially relevant are methods based on convolutional neural networks designed to solve various problems of image analysis, such as classification, segmentation, detection, anomaly search, etc. The absence of the need for algorithms to isolate and describe complex structures from the point of view of medical diagnosis and excellent generalizing ability make neural network methods of image analysis convenient and effective.

However, the principle of constructing features directly from images, which underlies modern convolutional neural networks, makes such neural network approaches extremely demanding on the quality and uniformity of the image sample on which the model is trained. Thus, an urgent task at the moment is to analyze the quality of images that fall into the input of the neural network model, which is used both in training and validation. Due to the features and wide range of settings of medical equipment, the problem of quality control of input images is relevant for various images, for example, for magnetic resonance imaging, computer, and radiography.

The processing of medical digital images has been the object of close attention of researchers over the past decades. Many works are devoted to the development/use of mathematical methods and software in this field, as well as the development (improvement) of hardware. The interest of researchers in modern means of processing X-ray medical images is due to the increased requirements for the quality and reliability of diagnostic systems being developed. One of the main applications of radiography in human medicine is the acquisition and analysis of chest images. At the same time, the main objectives of the analysis of such images are usually the isolation (segmentation) of acquired morphological formations and their attribution to known classes of pathologies. To solve the problems of pattern recognition based on the results of the analysis of raster halftone images, it is necessary to solve the problem of dividing the original image into parts (segments) that differ in their semantic content. The effectiveness of further image analysis and classification depends on the quality of the segmentation.

The difficulty of detecting Covid-19 infection at the initial stage is due to the great similarity of its symptoms with an infection caused by pneumonia. In this regard, the virus has spread quite quickly around the world. For this reason, the diagnosis of lung diseases has become the most urgent task not only for medical professionals but also for the entire population of our planet. The relevance and practical aspect of these problems are also related not only to the coronavirus pandemic but also due to the growth of the industry with unsatisfactory control of the release of harmful substances into the air, which increases the predisposition to diseases such as lung cancer, tuberculosis, pneumonia, and others. Therefore, there is a need for constant monitoring of the condition of the lungs to prevent or detect diseases before it causes severe damage to health.

Therefore, the immediate problem at the moment is rapid detection; and this is becoming increasingly important as the healthcare system becomes overwhelmed by the flow of patient data. The need to create an automated computerized process is becoming more and more obvious. With this in mind, it is proposed to use radiomic imaging features, using deep learning for this purpose.

Deep learning entails learning based on raw data to automatically discover the representations needed for detection or classification. In the context of medical images, it directly uses the pixel values of the images (instead of extracted or selected features) at the input; thus, manual errors caused by inaccurate segmentation or subsequent feature extraction are eliminated. Convolutional neural networks (CNNs) are one of the most popular deep learning models. A breakthrough in CNN occurred with the ImageNet competition in 2012, where the error rate in object recognition was almost halved.

It is expected that artificial intelligence algorithms, along with clinical and radiological functions obtained based on chest X-rays, will be of great help in conducting large-scale detection programs that can take place in any country with access to X-ray equipment and assistance in the effective diagnosis of Covid-19.

In this scenario, machine learning (ML) and deep learning (DL) offer fast, automated, and effective strategies for detecting abnormalities and extracting key features of the altered lung parenchyma that can be linked to specific Covid-19 virus signatures.

Radiography is technically the simplest and most accessible method of preliminary diagnosis of the disease for the population, including tracking the course of the disease. Medical specialists in the process of determining images in images when making decisions face many issues:

– incomplete and inaccurate initial information;

– large variability of attributes and small size of the selection.

The relevance of the topic of the work is associated with a significant spread of the phenomenon under study and lies in the need to develop recommendations for improving work in the field under consideration.

The object of the study is lung pathology.

The subject of the study is an X-ray divided into categories: healthy, patients with pneumonia, and patients with Covid-19.

During the pandemic, the issue of processing a large amount of data (X-rays and CT scans of the lungs), as well as the qualitative and rapid classification of these data, became acute. Machine learning methods are used to solve this problem. Neural networks are trained on large amounts of data and, subsequently, give their guess on new similar data, which facilitates the work of doctors, helping them to make a diagnosis more correctly. Recognition of functional diagnostic images is currently an urgent task, as it is directly related to the pandemic and its consequences.

## 2. Literature review and problem statement

In [1], machine learning algorithms have become very important in the medical sector, especially for diagnosing diseases from a medical database. Many companies use these methods for early disease prediction and to improve medical diagnosis. The work is to give an overview of machine learning algorithms that are used to identify and predict many diseases, such as naive Bayes, logistic regression, support vector machine, K-nearest neighbors, K-means clustering, decision tree and random forest. This paper reviewed many previous studies that have used machine learning algorithms to identify various medical conditions over the past three years.

In [2], the terminology of the problem of X-ray and CT image recognition using deep machine learning techniques was described, the relevance of the problem was reviewed, and the current state of the problem in the field of X-ray CT recognition was analyzed. Aspects of the problem to be solved, identified in the analysis, are recorded in the form of problems to be solved, procedures, models and methods, information technologies used, tools and software solutions to the problem.

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 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 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] the results of developing a module of expert system for diagnosing diseases based on the neural network analysis method are considered. It has been established that convolutional neural networks have maximum efficiency in processing images of magnetic resonance imaging devices. An algorithm for choosing the optimal structure of a neural network in the format of the task was formed. The result of this work is a generated convolutional neural network capable of detecting foci of pathological tissue changes on MR images with a high degree of probability.

In [5] the process of detecting pathological changes in lungs based on joint analysis of radiological reports and tomographic images is described. Approaches to automation of area of interest selection on lung CT images are compared. It is said that the Otsu method allows isolating a lung region with a sufficient degree of reliability, while the use of convolutional neural networks for this task is not fully justified. Also as an alternative, it is proposed to use the technology of selecting regions of interest, which is based on the optimization of the quality criterion for the subsequent classification of lung CT images. It is concluded that improving the quality of automatic diagnostics based on digital images through the use of radiological reports is an extremely urgent task.

The author in [6] reviews the problems and methods of machine classification and X-ray image recognition (CXR), as well as the issues of improving artificial NS that are used to improve the quality of classification of radiological syndromes. It is noted that NSs are ideal for disease recognition using scans, as there is no need to provide a specific algorithm for disease detection. It is established that current methods for detecting anomalies (diseases) in CXR have difficulties with insufficient training data, standardization of images and pre-segmentation of the training set. Specific ways of solving the described problems faced by NSs in data analysis are formulated. As a solution, the use of deep learning techniques, namely convolutional NSs based on backward error propagation and gradient descent with prior segmentation of the training sample and the application of transfer learning to categorize diseases in medical images are proposed. An intelligent system architecture is developed that can recognize abnormalities in CXR at the physician and radiologist levels using a deep learning environment. It is concluded that despite the promising results of intelligent systems, serious problems remain, especially concerning a theoretical framework that would clearly explain how to determine the optimal choice of model, type and structure for a particular task or for a deep understanding of why a particular architecture or algorithm is effective in that task.

In [7], an idea is described that is based on methods for finding singular points, which are used in face recognition, image comparison, etc. To implement it used one of the methods of computer vision - the method of SURF (Speeded Up Robust Features). The SURF method is used to find the characteristic points of the image. The output is an X-ray image with the areas of possible pathologies marked on it. However, it is noted that for all the advantages of the method, the main problem is its accuracy; here let's mean not the accuracy of pathology detection, but the accuracy of matching characteristic points.

The construction of a machine learning model using the ML.NET Model Builder platform is described in [8]. It is noted that the Deep Neural Network (DNN – Deep Neural Network) model proved to be the most optimal for solving the recognition problem.

In [9], it is argued that the rapid development of CT-based lung cancer diagnostic systems is due to the creation of super-precise neural networks (SNNs). The stages of the CT-image-based lung cancer detection procedure are described: data collection, image preprocessing, segmentation, formation detection, reduction of false-positive cases, and classification of neoplasms. Examples are given of the currently developed fully automated lung cancer diagnostic systems: Deep Lung and Nodule X. It is concluded that acting as an assistant, AI will allow the diagnostician to make more informed decisions, relieving it from a lot of routine work.

In [10] the learning process of the neural network (deep superfine neural network), the architecture of the developed module (the software module is a deep learning neural network based on the convolutional neural network CNN technology), its operation algorithm, and the structure of the neural network underlying it and analyzing the images are considered. The results of computational experiments on using the model to analyze a real sample of data are presented.

It is concluded that the experiments have confirmed the prospects of using a neural network for solving the task of automatic analysis of fluorographic X-ray images for the detection of pathologies. At the same time, increasing the level of confidence in the network reduces the number of errors, but reduces the efficiency of using the system. It is emphasized that to improve the performance of the system – to reduce the number of errors and to increase X-ray imaging, it is advisable to use a larger database of images for training the neural network.

All this allows to assert that it is expedient to conduct a theoretical and applied research on improving algorithms related to the use of neural networks within a unified computing technology for solving problems of assessing the condition of an object in medical images.

## 3. The aim and objectives of the study

The aim of this study is to identify and classify objects in real time using neural networks on a mobile platform, including in the field of Medicine, where X-rays study the results of chest diseases at an effective level thanks to special machine learning.

To achieve the aim, the following objectives were set:

– identification of informative features using neural networks for automatic description of X-ray images;

– implement and test the selected methods of X-ray images.

## 4. Materials and methods

In order to search for various lung pathologies on fluorographic images (for example, tuberculosis), it is possible to learn how to isolate the lungs themselves on the images. This is important, because in the future machine learning algorithms will be used to recognize diseases. If do not identify the light ones, but use the whole images for training, then it is possible to risk giving extra data to the algorithm input, among which the classifier will look for signs for training. In addition, the allocation of lungs will reduce the amount of hardware resources required for training and the amount of time spent on training. Of course, on a small training sample, it is easiest to select the lungs manually. However, when to work with a large sample of images, it is necessary to use computer recognition algorithms.

The first method is an expert system that works according to a simple algorithm (without using any machine learning algorithms).

Its description can be set using the following sequential steps:

– highlighting the contour of the lungs using color. At this stage, the contours of the body are also highlighted;

– clipping body boundaries using analyzed histograms for rows and columns of the image;

– repeated analysis of histograms for more accurate removal of unnecessary parts.

In writing, the remaining selected parts of the image into a rectangle. It is assumed that only this point has allocated the lungs [11].

This algorithm performs well on most images. However, it malfunctions for some images, for example, when the power of the fluorography apparatus was reduced for the patient in order to reduce radiation due to frequent fluorography procedures. Also, the rectangular shape is not good enough for further analysis – due to the fact that not only the lungs are included in the rectangle, and often no more lungs than lungs are included in the rectangle, due to the anatomical shape of the human respiratory organs.

Special radiological research methods Special radiological research methods are conveniently divided into groups of the same type for their intended purpose:

1. Methods of artificial contrast (direct and indirect contrast).

2. Methods regulating the size of the resulting image (telerentgenography and direct magnification of the X-ray image).

3. Methods of spatial research (linear and computed tomography, panoramic tomography, panoramic zonography).

4. Methods of registering movements.

*Artificial contrast techniques.*

With a conventional X-ray examination, it is easy to obtain an image of organs that absorb X-rays to varying degrees; such organs have a natural contrast. For example, bones that are well defined by conventional radiography. However, conventional radiography cannot provide different images of organs and tissues having approximately the same ability to absorb X-rays. Thus, the contours of the heart are visible on the overview image of the chest cavity, but it is impossible to distinguish its chambers filled with blood, since blood and heart muscle equally delay X-rays. This applies to all soft-tissue structures of the body. In order to differentiate tissues that have the same ability to delay X-rays, artificial contrast is used. Substances capable of absorbing X-ray radiation stronger or weaker than soft tissues are injected into the body, which makes it possible to achieve the necessary contrast of the studied organs. There are 2 groups of artificial contrast: direct and indirect contrast methods. Direct contrast is based on the introduction of a contrast agent directly into the cavity of the organ under study or into the surrounding cavity, tissue. For example, methods of studying the organs of the gastrointestinal tract, blood vessels, uterus, salivary glands, fistula passages, etc. Indirect contrast is based on the ability of some organs to selectively capture a contrast agent from the blood, concentrate it and remove it with its physiological secret. For example – liver, gallbladder, kidneys. After the introduction of such substances, after a certain time, during X-ray examination, it is possible to distinguish the patient's bile ducts, gallbladder, renal cavity system, ureters, and bladder. Artificial contrast techniques have significantly expanded the possibilities of X-ray research methods in various fields of medicine [12].

## 5. The result of the research is the application of mathematical methods and machine learning algorithms for clustering X-ray images

### 5. 1. The separation of informative features using neural networks for automatic description of X-ray images

The invention relates to methods of digital image processing and can be used in intelligent classification systems for X-ray images. The technical result is to increase the accuracy of recognizing areas of interest when analyzing graphic information. This result is achieved by the method of automatic classification of X-ray images using transparency masks, which provides for the formation of an X-ray digital image in the form of a matrix of optical densities of the object, obtaining deep layers of the image by processing the original digital image with local filters unique to each layer, reducing the dimensionality of images in deep layers through the technology of pooling (sub discretization), formation of a space of informative features for a fully connected neural network to be trained from sub discretized deep layers and classification of the resulting vector of informative features by means of a fully connected neural network.

The task is achieved by the fact that in the well-known method of automatic classification of X-ray images, which provides for the formation of an X-ray digital image in the form of a matrix of optical densities of an object, obtaining image layers (depth dimension) by processing the original digital image with local filters unique to each layer, followed by a reduction in the dimension of images in the deep layers using pooling technology (sub discretization), formation of a space of informative features for a fully connected neural network being trained by scanning deep layers, training of a fully connected neural network using examples of X-ray images with specified morphological formations; the input digital image is supplemented with a transparency mask, local filters are implemented in the form of identical operators that form deep layers by indexing the scale of the filter mask. At the same time, the pooling technology is carried out by forming three-dimensional tensors, two for each deep layer, by processing the deep layers with two differential operators, the number of elements of which is determined by the scale of the deep layer, with binary outputs and a threshold activation function, while each scale will be characterized by three-dimensional megapixels, the number of which is determined by the scale mask of the corresponding deep layer.

Automatic analysis as a medical diagnostic term means automatic classification, or image recognition in particular cases. The image belongs to a certain group or class, as an example – norm or pathology. Classification in mathematical essence is understood as finding a certain function that should display a set of images in such a set, the elements of which are represented by classes or groups of images.

The automatic classification process most often takes place in three stages:

– the first stage includes preprocessing, which is the maximum reduction of the images under consideration to the reference or normalized ones. Often in medical images, these are various shifts, brightness changes, as well as contrast changes and geometry transformations (scale change, axis deviation);

– the second stage relates to the selection of features, with the help of which the function, which is a processed image, is subjected to a functional transformation, which allocates quite a lot of the most significant features encoded by real numbers. The selection of features consists in numerous mathematical transformations of the image;

– the third stage is a classification of features. The set of real numbers eventually obtained from the previous operations and which describes the selected features is compared with the reference numbers that are stored in the machine's memory. An electronic computer, as a result of such a comparison, can classify images, i. e. refer them to any of the well-known types, for example, norm or pathology.

However, there are several circumstances that make it too difficult to perform the two extreme stages of automatic classification, such as:

1) the absence of a standard norm due to the individual characteristics of any organism;

2) the unreality of the formation of a standard of pathology, despite the fact that there is a very wide variety of its forms.

Therefore, full automatic classification is currently not possible with differential diagnosis. It should be noted that only a preliminary selection can be carried out according to the norm-pathology principle, which replace the initial step in the evaluation of the image. Despite this, this step will be very useful in the case when mass dispensary examinations are carried out. To solve the problem of automatic image classification, block diagrams of the learning algorithm presented in Fig. 1 and image classification presented in Fig. 2 were developed.

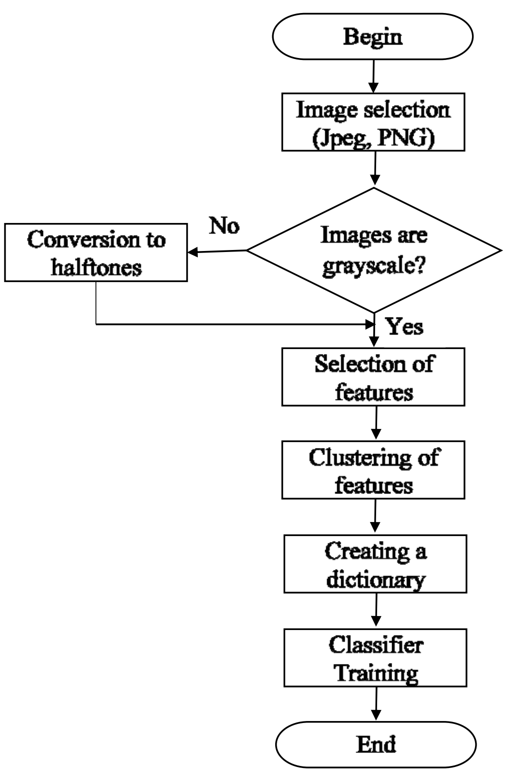



Fig. 1. Block diagrams of the learning algorithm

Classifier training consists of:
– loading a database with images for classifier training;
– image type checks;
– feature extraction by SURF method;
– clustering by k-means method;
– generating a dictionary from clusters.

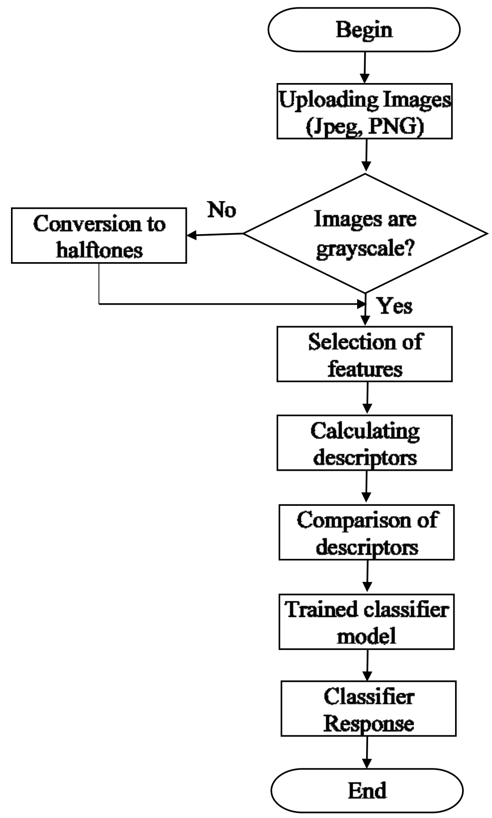



Fig. 2. Block diagram of the classification algorithm

Image recognition consists of:
– image loading;
– image type checks;
– selection of SURF features;
– dictionary comparisons;
– classification of the image.

The development of machine learning algorithms provides ample opportunities in the field of automation of biomedical tasks. Computer processing of biomedical images increases the accuracy of image analysis, reduces the role of the human factor in decision-making, allows to evaluate the effectiveness of therapy and generally improves the quality of life of people. Biomedical research in the field of analysis and recognition of images obtained during functional diagnostics is actively developing.

In this paper, based on scientific publications, an analysis of the application of currently existing methods for recognizing images of functional diagnostics is carried out.

**5. 2. Implementation and testing of selected methods of X-ray images**

Modern highly efficient compression algorithms for image processing are based mainly on methods of wavelet analysis, among which the classical orthogonal Haar basis occupies a prominent place. The Haar function, like the Walsh function, belong to the class of piecewise constant functions. Their difference from Walsh functions is that they are localized on separate parts of the studied interval. Therefore, Haar functions that allow to evaluate the local properties of the signals under study are often called Haar wavelets.

The system was first built and began to be studied in 1910 by A. Haar. The Haar system consists of piecewise constant functions defined on the interval [0,1).

The Haar transformation is based on the orthogonal Haar matrix. The first function of the Haar system is constantly:

$$\alpha_0(\theta)=1,\quad \theta\in[0,1).$$

It is convenient to build the rest of the functions of the Haar system by groups: a group with numbers $m$ contains $2^m$ functions.

$$\alpha_{mk}(\theta),\quad m=1,2,\ldots,\quad k=0,1,\ldots,2^m-1.$$

The following formula is used to normalize the Haar function:

$$\alpha_{mk}(\theta)=\begin{cases}\sqrt{2^m}, & \theta\in\left[\dfrac{k}{2^m},\dfrac{k+1/2}{2^m}\right),\\ -\sqrt{2^m}, & \theta\in\left[\dfrac{k+1/2}{2^m},\dfrac{k+1}{2^m}\right),\\ 0, & \theta\in\left[\dfrac{k}{2^m},\dfrac{k+1}{2^m}\right).\end{cases}$$

Below are examples of orthonormal Haar matrices of the fourth and eighth order

$$H_4=\frac{1}{\sqrt{4}}\begin{pmatrix}1&1&1&1\\1&1&-1&-1\\\sqrt{2}&-\sqrt{2}&0&0\\0&0&\sqrt{2}&-\sqrt{2}\end{pmatrix},$$

$$H_8=\frac{1}{\sqrt{8}}\times$$
$$\times\begin{pmatrix}1&1&1&1&1&1&1&1\\1&1&1&1&-1&-1&-1&-1\\\sqrt{2}&\sqrt{2}&-\sqrt{2}&-\sqrt{2}&0&0&0&0\\0&0&0&0&\sqrt{2}&\sqrt{2}&-\sqrt{2}&-\sqrt{2}\\2&-2&0&0&0&0&0&0\\0&0&2&-2&0&0&0&0\\0&0&0&0&2&-2&0&0\\0&0&0&0&0&0&2&-2\end{pmatrix}.$$

Higher-order Haar matrices are constructed according to the same rules as the $H_4$ and $H_8$ matrices. The Haar transform can be considered as the process of sampling the original signal, in which the sampling step is halved with the transition to the next line.

The is Dobshaw-4 transformation. The Dobshy-4 transformation is given by [4, 5] using the following matrix

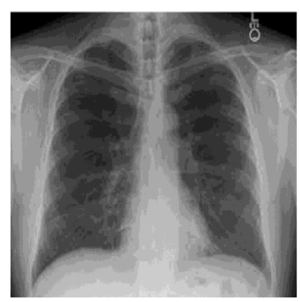
$$M=\sqrt{2}\begin{bmatrix}h_0&h_1&h_2&h_3&&&&\\&&h_0&h_1&h_2&h_3&&\\&&&&h_0&h_1&h_2&h_3\\h_2&h_3&&&&&h_0&h_1\\h_3&-h_2&h_1&-h_0&&&&\\&&h_3&-h_2&h_1&-h_0&&\\&&&&h_3&-h_2&h_1&-h_0\\h_1&-h_0&&&&&h_3&-h_2\end{bmatrix}.$$

The elements of the matrix are calculated using the formulas given below: $h_0=\left(1+\sqrt{3}\right)/8$, $h_1=\left(3+\sqrt{3}\right)/8$, $h_2=\left(3-\sqrt{3}\right)/8$, $h_3=\left(1-\sqrt{3}\right)/8$.

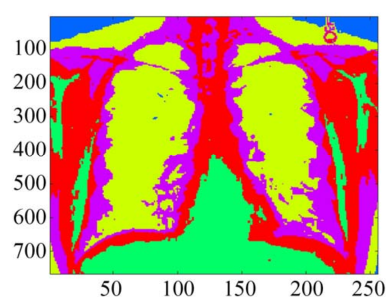
*Clustering by transformation coefficients.*

This method is programmatically implemented in the MatLab environment and image analysis is performed. Images are divided into separate sections by software. It is possible to apply various non-standard approaches to the study of textures using orthogonal transformations. For example, the original image is split into disjoint square windows. For example, a window with a size of 8×8 was used. Next,there is an integral transformation in each window. At the same time, it is possible to reset some spectral coefficients, for example, high-frequency ones, or in several specific parts of the spectrum. In the two-dimensional case, the frequency spectra are two-dimensional matrices. It is possible to arrange matrix elements in vectors. For example, the rows of the matrix can be placed sequentially one after another. In principle, the positions in the vector in which we have zeroed out the spectral coefficients can be deleted from the resulting vector. Next, the clustering procedure can be carried out according to the available vectors.

Below are the results of image processing (Fig. 3) by the method described above.



*a*




*b*

Fig. 3. Image processing: *a* – the original image, clustering along the low-frequency part of the spectrum, the number of clusters is 3; *b* – the Haar transform is applied; the window size is 8×8

In the future, to determine the pathology in the chest, it will be possible to use machine learning algorithms, for example, based on a neurocomputer approach.

Computer vision is a field of artificial intelligence (AI) that allows computers and systems to extract meaningful information from digital images, images, and other visual inputs and perform actions or make recommendations based on that information.

Computer vision requires a lot of data. It analyzes the data over and over again until it detects differences and eventually recognizes the images.

Convolutional Neural Network (CNN), also known as ConvNet, is a type of artificial neural network (ANN) whose architecture is deep and has amazing generalization capabilities compared to other networks with FC layers.

The corona-Covid-19 virus affects the respiratory system of healthy people, and chest X-rays are one of the most important imaging methods for detecting coronavirus. A machine learning model will be developed to classify X-rays of healthy and pneumonia (Corona) affected patients through the chest X-ray data collection, and this model will provide power to the AI application to test the corona virus in a faster phase [13].

Collection of images of chest X-rays of patients who are healthy and affected by the Covid-19 virus (Corona), infected patients names and signs of images are shown in Kaggle.com taken from the world database. The symbols and symbols of the images are special ChestXrayCorona_Metadata. saved in csv file.

As shown in Fig. 4, the workflow of this study begins with the collection of primary data sets that include two image classes: one class belongs to chest X-rays of confirmed cases of Covid-19, and the other class of images belongs to ordinary people who do not have the virus. At the next stage of the study, interested medical professionals analyzed the data set and removed some of the X-ray images that were not clear in terms of quality and diagnostic parameters. Thus, the data collection obtained was very clean, since each X-ray image was of good quality and, according to their examination, clear in terms of important diagnostic parameters. At the third stage, the data set was supplemented by using standard zoom methods to increase the size. The resulting data collection was used to train the model at the next stage. After training, the model was tested for performance in detecting the disease. Testing of the proposed CNN model was done using a test data set from the original data set, as well as an independent verification data set. The total number of X-ray images in the training kit, the test kit, the validation kit, and the share of X-ray images in the two predictive classes are included in the data set data obtained from the previously mentioned kaggle data collection.

Two different methods were used in machine learning:

– CNN;

– MobileNetV2.

CNN is a Class of neural networks that specialize in processing data with a grid-like topology, such as images, also known as convolutional neural networks or ConvNet. During training, it can use hundreds or thousands of hidden layers.

The proposed CNN model consists of 38 layers, 6 of which are convolutional (Conv2D), 6 maximum convolution layers, 6 capture layers, 8 activation function layers, 8 batch normalization layers, 1 smoothing layer, and 3 fully connected layers; The Shape of the input image of the CNN model (150, 150, 3), i. e. 150 to 150 RGB images. All Con2D layers used a 3×3 core, but after each two Con2D layers, the filter size increases. The 1st and 2nd layers of Con2D used 64 filters to learn from the input, while the 3rd and 4th layers of Con2D used 128 filters, and the 5th and 6th layers used 256 filters. After each Con2D layer, a maximum merge layer with a merge size of 2×2 was used, the package normalization layer was used with the axis =–1 argument, the activation level was used with the ReLU function, and the capture layer. Used with a dropout rate of 20 %. The output of the 256 output neurons of the last Con2D layer continues with the maximum accumulation, packet normalization, activation, and capture layer. Since the final conjugation and convolutional layer give a three-dimensional matrix as the output, a smoothing layer was used to smooth the Matrix, converting them to a vector that is introduced into 3 dense layers [14].

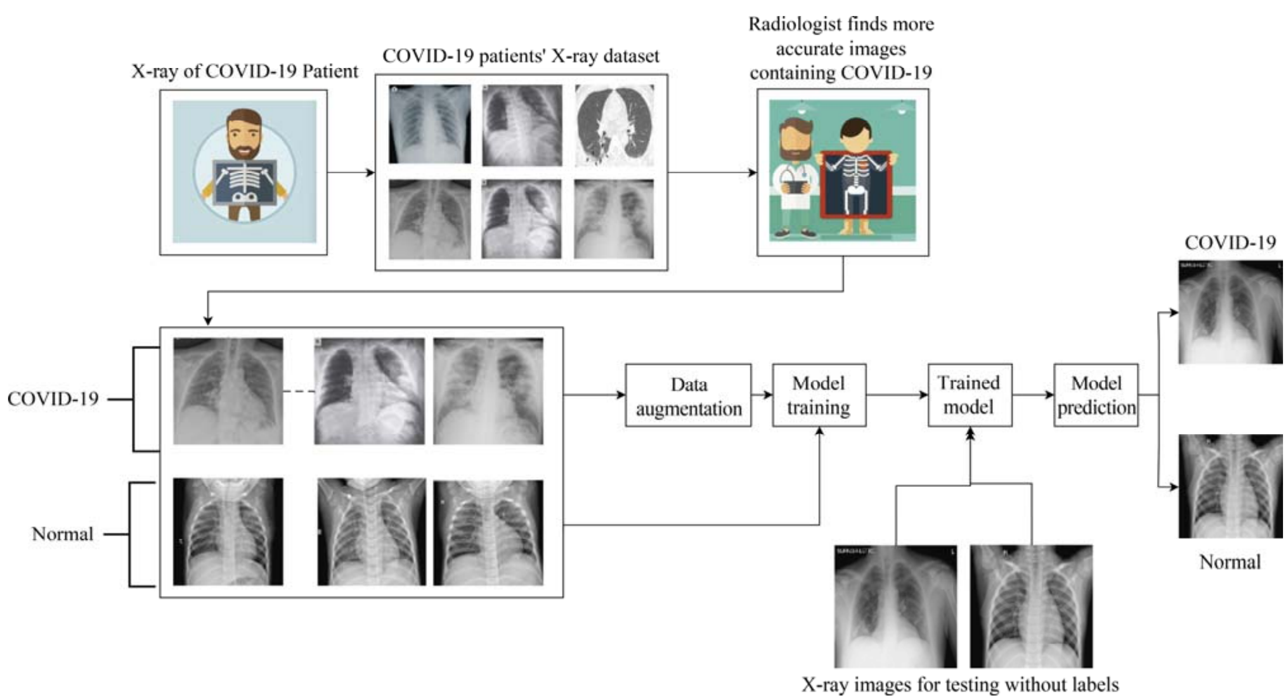



Fig. 4. Processes performed in machine learning

This study uses CNN for binary classification; this is the reason for using the binary cross-entropy (BCE) loss function. Since binary classification requires only one output node to classify data into one of the two specified classes, in the case of the BCE loss function, the output value is passed to the Sigma activation function. The output given by the Sigma activation function is between 0 and 1. It finds an error between the Predicted class and the actual class. To reduce the loss of the learning model, a "Adam" optimizer was used, which changed the attribute weight and learning speed. The values of the model parameter are in Table 1.

Table 1

Model parameter

| Parameter | Value |
|---|---|
| Input dimension | (150, 150, 3) |
| Filter to learn | 64, 128, 256 |
| Max pooling | 2 × 2 |
| Batch normalization | Axis=–1 |
| Activation functions | ReLU, sigmoid |
| Dropout rate | 20 % |
| Kernel size | 3×3 |
| Epochs | 50 |
| Optimizer | Adam |
| Loss function | binary_crossentropy |

During the initial experiments, CNN was used with different configurations in terms of using a series of convulsion layers in the model. The decision on how many convulsion layers were used in the model was made using an incremental approach. First, CNN was tested using only one convolutional layer, and the results were analyzed. CNN was then built in two layers and the results were analyzed, etc.the approach continued until the results presented by the model were accurate and effective. The final model, which was very possible according to the results, consisted of six layers of convulsions.

MobileNetV2-parameterized small, low-latency, low-power models that meet the resource constraints of various use cases. They can be created in the same way as other popular large-scale models for classification, definition, embedding, and segmentation.

The MobileNetV2 architecture uses deeply divergent convolutions that require significantly less computing power than standard convolutions. Despite being significantly lighter and more efficient than most well-established networks, MobileNetV2 is just as accurate as other modern models like VGG16 and GoogleNet. MobileNetV2 uses 53 convolution layers with a package normalization function and a ReLU activation function after each layer [15].

It is possible to see the image of a clear chest X-ray image shown in Fig. 5. This image is converted to a common gray color palette. The difference between the main healthy and diseased chest is distinguished by the fact that X-rays pass through the body and the whitish areas of the finished output image. Since it is difficult to observe with the naked eye, let's turn this image into a digital matrix. Each pixel is represented by a number from 0 to 255.


Fig. 5. Clear chest image

In numerical form, it is possible to see the histogram type shown in Fig. 5. As it is possible to see, in a histogram image, it is possible to see that there are more than 20,000 pixels in the total image from the numbers located along the $Y$-axis of the histogram. And the $X$-axis is represented by pixel-value numbers. Using this histogram, it is possible tomake sure that the chest shown in Fig. 6 is clean and prove that it is not affected by any disease.

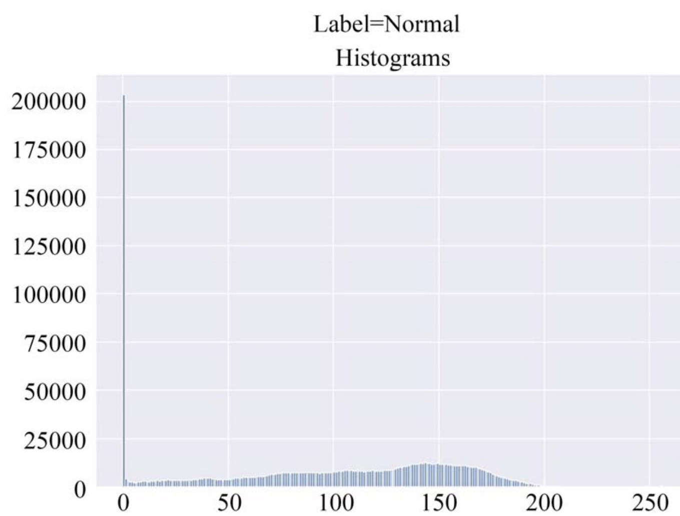



Fig. 6. Histogram image of a clean breast

The following Fig. 7 shows an X-ray of the chest affected by pneumonia. It is according to the previous algorithm that to turn it into a digital Maritsa and turn it into a single-line array. The Fig. 7 shows which area of the chest is affected by the arrows.

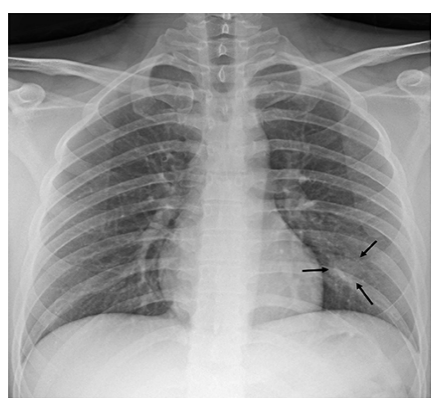


Fig. 7. X-ray image of the chest where the disease is detected

Turning Fig. 8 into a digital array, let's turn it into a gitogram image using the previous algorithm. As it is possible to see on the histogram, the number of white pixels is more common between 50 and 250. This is due to the fact that X-rays do not pass through a single body. Identified whitish spots are characterized as signs of the disease.

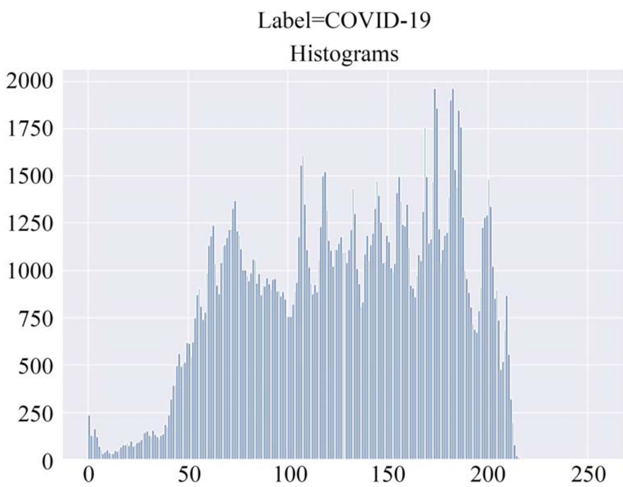



Fig. 8. Histogram image of the affected chest

Android TensorFlow Lite machine learning. Using the TensorFlow Lite library to identify an object TensorFlow Lite is a lightweight TensorFlow solution for mobile devices.

TensorFlow Lite is better because:

– TensorFlow Lite allows to run machine learning on your device with low latency. So it's fast;

– TensorFlow Lite gets a small binary size. So it's good for mobile devices;

– TensorFlow Lite also supports hardware acceleration via the Android Neural Networks API.

TensorFlow Lite uses many methods to achieve low latency, such as:

– core optimization for mobile applications;

– pre-integrated activations;

– quantized cores (fixed point math) that allow smaller and faster samples.

*How to use TensorFlow Lite in your Android app.*

The most important difficult part of using TensorFlow Lite is using a template that differs from the normal TensorFlow template (.tflite) is the preparation of.

To run a model using TensorFlow Lite, use the model that TensorFlow Lite accepts (.tflite) conversion required. From here, follow the instructions.

Now you have a sample (.tflite) and has a label file. You can start using these template and label files in the Android app to download the model and predict the result using the TensorFlow Lite library.

TensorFlow Lite is a lightweight version of TensorFlow and its goals are embedded and mobile devices. With this version of the frame, trained models consume less resources and require less space savings. Thus, it takes less final time to determine. This performance was achieved thanks to methods such as pre-melt activation and quantized nuclei. In addition to the new techniques introduced.

TFLite framework also defines a new sample file format based on FlatBuffers open source analysis library. It is a buffer similar to the format used by the TensorFlow protocol, but with an improved parsing/unpacking step for faster and more efficient data access by skipping it. Finally, TFLite uses a new user interpreter that prevents any unnecessary memory allocation or initialization to improve execution time. (TensorFlow n.d. d, quoted on Page 1) to use TFLite, there is no need to retrain the model used by the TensorFlow Mobile device since the user only needs to convert the current model with a tool called TOCO finally get the TensorFlow Lite FlatBuffer file. After using the new file, it is processed by the TensorFlow Lite interpreter [16].

Fig. 9 shows 3.0 iterations of the CNN test processes with a maximum probability of success of 95.65 %.

To test the trained model, 400 drawings were given, and after passing the Illustrated model, a comparison work was performed on the square graph shown in Fig. 10. As it is possible to see, out of 400 images in the collection of images, 377 images of pure breasts were found, which is 94.2 %. The values located in the Positive Cube are given, the number of images that determine the type of disease, and the percentage size.

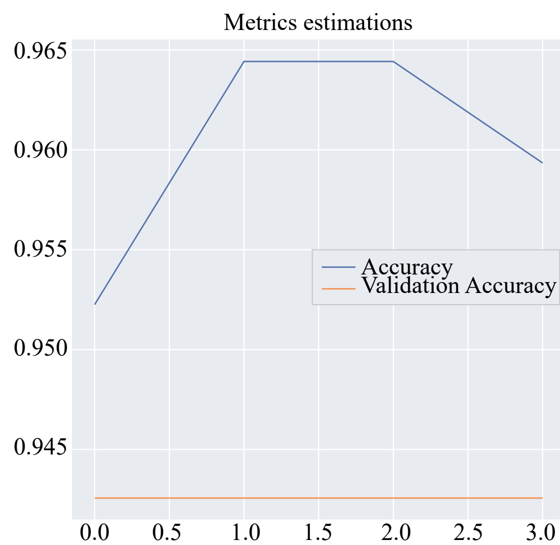



Fig. 9. Recording graph in the course of learning the convolutional neural networks

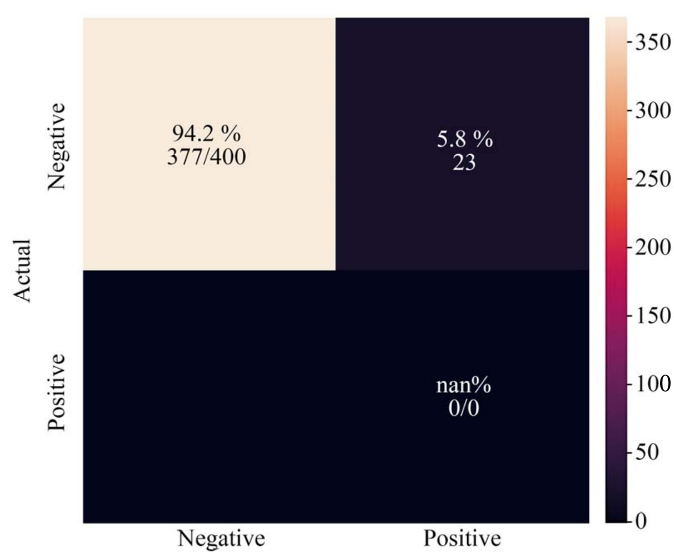



Fig. 10. Comparative graph of the model test result

The same result can be seen in Fig. 11 of the MobileNetV2 network, out of the 400 images obtained during testing, 377 were identified as pure, and the remaining 23 images were identified as diseased breasts.

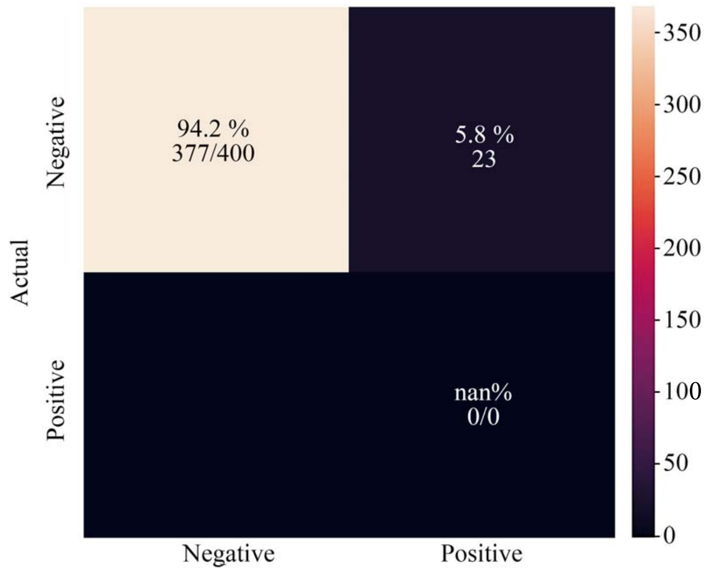



Fig. 11. Test result of MobileNetV2 network

In the course of using both methods, both showed a high degree of accuracy, giving 100 percent accuracy in the detection of the disease. Using both methods, a mobile application for breast examination was developed in Fig. 12.

*Android TensorFlow Lite machine learning.*

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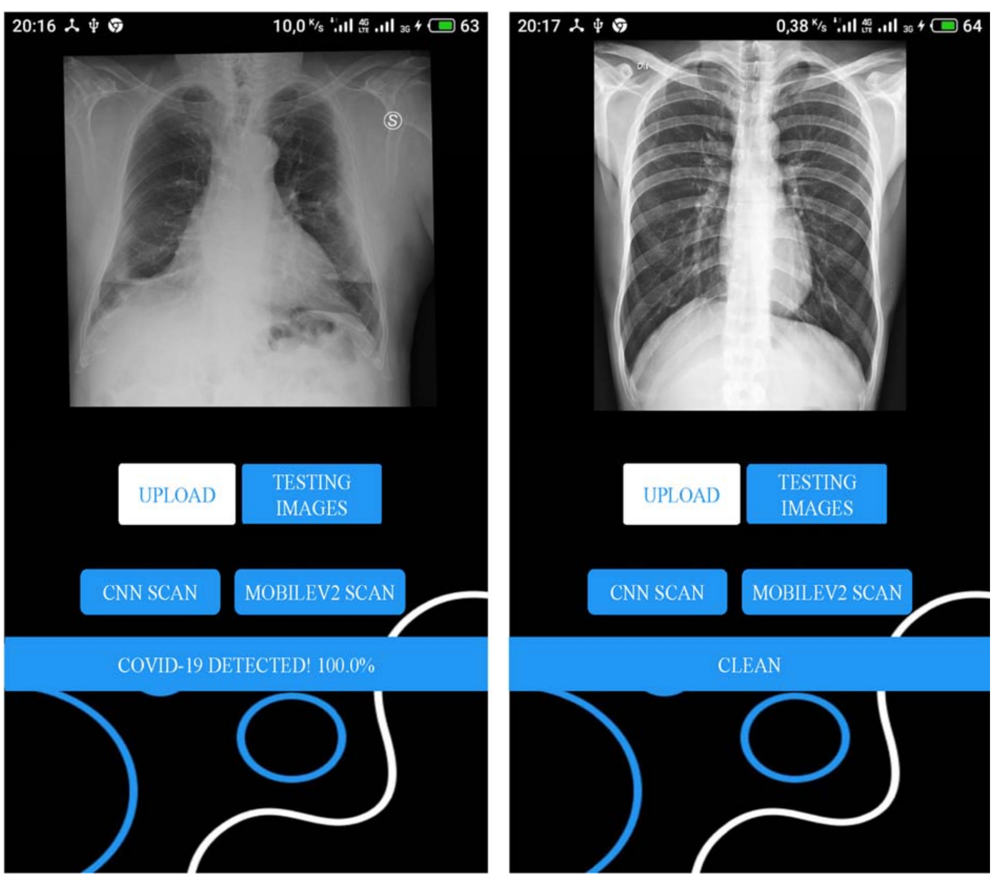


Fig. 12. Topological mobile application for Breast Examination

## 6. Discussion of experimental results application of mathematical methods and machine learning algorithms for clustering X-ray images

In this paper, a CN-based machine learning approach using transfer learning is presented to distinguish patients with COVID-19 (viral pneumonia) from bacterial pneumonia, and healthy patients. Twenty pre-trained CNN models were deployed to study transfer learning and it was concluded that the exact tuning of pre-trained CNN models can be successfully determined with an accuracy of 94.27 %. Healthy images show uniformity in the chest using the Haar method (Fig. 3.)

The structural advantages of various deep learning models are analyzed and it is concluded that MobileNet is a suitable model for diagnosing pneumonia from clinical images. In addition, the improved structure of the Mobile Net network to improve accuracy is used. To confirm the theoretical results, let's use conventional convolution and four other basic network models to classify and identify the same datasets of pneumonia X-rays that were obtained in reality. After comparing their accuracy and other performance indicators, it turns out that the improved MobileNet gives better results than other CNN.

There are several limitations in this one that can be overcome in future research. In particular, deeper analysis requires much more data on patients, especially those suffering from Covid-19. A more interesting approach for future research will focus on distinguishing patients with mild symptoms rather than symptoms of pneumonia, while these symptoms may not be accurately visualized on X-rays or may not be visualized at all.

In addition, these methods can be used on larger datasets to solve other medical problems, such as cancer, tumors, etc., as well as in other areas of computer vision, such as energy, agriculture and transportation in the near future. Early diagnosis of patients with COVID-19 is important to prevent the spread of the disease to others.

In the future, in the following articles, we will conduct research using other types of machine learning in our research work.

## 7. Conclusions

1. The use of various methods of pre-processing of lung X-rays makes it possible to improve the final quality of recognition of anomalies in the chest. The preprocessing stage is one of the most significant in the automated analysis of X-ray images.

2. Healthy images show uniformity in the chest using the Haar method. Health improvements show uniformity in breast cells using the Haara method. By developing a mobile application using machine learning, it was able to determine that 94.27 percent of human chest X-rays were detected in the study.

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References

1. Ibrahim, I., Abdulazeez, A. (2021). The Role of Machine Learning Algorithms for Diagnosing Diseases. Journal of Applied Science and Technology Trends, 2(01), 10–19. doi:https://doi.org/10.38094/jastt20179
2. Ziyazetdinova, L. Yu. (2021). Analiz sostoyaniya issledovaniy v oblasti raspoznavaniya rentgenovskikh i kt snimkov s pomosch'yu metodov glubokogo mashinnogo obucheniya. Mavlyutovskie chteniyamaterialy XV Vserossiyskoy molodezhnoy nauchnoy konferentsii. Ufa, 235–245.
3. Pechnikov, A. A., Bogdanov, N. A. (2021). Comparison of two approaches to the recognition of pneumonia by X-rays.Petrozavodsk, 90–91. Available at: https://www.researchgate.net/profile/Surovtsova-Tatyana-2/publication/357340485_Development_of_evaluation_criteria_for_a_creative_programming_competition/links/61c98658d4500608166e8156/Development-of-evaluation-criteria-for-a-creative-programming-competition.pdf
4. Vasilchenko, V. A., Burkovskiy, V. L., Danilov, A. D. (2019).Algorithmization of the process of recognition of states of living objects based on special x-ray images. ComputerOptics, 43 (2), 296–303.doi: https://doi.org/10.18287/2412-6179-2017-43-2-296-303
5. Sludnova, A. A., Shutko, V. V., Gaidel, A. V., Zelter, P. M., Kapishnikov, A. V., Nikonorov, A. V. (2021). Identification of pathological changes in the lungs using an analysis of radiological reports and tomographic images. Computer Optics, 45 (2), 261–266. doi: https://doi.org/10.18287/2412-6179-co-793
6. Hrytsai, A.S., Levitskaya, T. A. (2019).Intelligentsystemfordetectinganomaliesin X-rayimagesusingdeeplearningmethods. Visnyk of Kherson National Technical University, 3 (70), 97–102. doi: https://doi.org/10.35546/kntu2078-4481.2019.3.10
7. Gorelov, I. A.,Nemtinov, V.A. (2016). Applicationofcomputervisiontechnologyinsearchofpathologieson X-rayimagesofchest. Wschodnioeuropejskie Czasopismo Naukowe, 7, 6–13. Available at: https://cyberleninka.ru/article/n/primenenie-tehnologiy-kompyuternogo-zreniya-pri-poiske-patologiy-na-rentgenogrammah-organov-grudnoy-kletki
8. Kuznetsov, N. A. (2020). Primenenie neyronnykh setey dlya diagnostiki zabolevaniy. Inzhenernye i informatsionnye tekhnologii, ekonomika i menedzhment v promyshlennosti: Sbornik nauchnykh statey po itogam vtoroy mezhdunarodnoy nauchnoy konferentsii. Volgograd: Obschestvo s ogranichennoy otvetstvennost'yu "KONVERT", 240–242.
9. Meldo, A. A., Utkin, L. V., Moiseyenko, V. M. (2018). XXI century diagnostic algorithms. Artifitial intelligance in lung cancer detection. Practical Oncology, 19(3), 292–298. doi:https://doi.org/10.31917/1903292

10. Minyazev, R. Sh., Rumyantsev, A. A., Dyganov, S. A., Baev, A. A. (2018). Analiz rentgenovskikh izobrazheniy dlya vyyavleniya patologiy s ispol'zovaniem neyronnykh setey. Izvestiya Rossiyskoy Akademii Nauk. Seriya Fizicheskaya, 82(12), 1685–1688. doi:https://doi.org/10.1134/s036767651812013x
11. Maurya, L., Mahapatra, P. K., Kumar, A. (2017). A social spider optimized image fusion approach for contrast enhancement and brightness preservation. Applied Soft Computing, 52, 575–592. doi:https://doi.org/10.1016/j.asoc.2016.10.012
12. Kim, S. E., Jeon, J. J., Eom, I. K. (2016). Image contrast enhancement using entropy scaling in wavelet domain. Signal Processing, 127, 1–11. doi:https://doi.org/10.1016/j.sigpro.2016.02.016
13. Lidong, H., Wei, Z., Jun, W., Zebin, S. (2015). Combination of contrast limited adaptive histogram equalisation and discrete wavelet transform for image enhancement. IET Image Processing, 9(10), 908–915. doi:https://doi.org/10.1049/iet-ipr.2015.0150
14. Tiwari, M., Gupta, B., Shrivastava, M. (2015). High-speed quantile-based histogram equalisation for brightness preservation and contrast enhancement. IET Image Processing, 9(1), 80–89. doi:https://doi.org/10.1049/iet-ipr.2013.0778
15. Wei, Z., Lidong, H., Jun, W., Zebin, S. (2015). Entropy maximisation histogram modification scheme for image enhancement. IET Image Processing, 9(3), 226–235. doi:https://doi.org/10.1049/iet-ipr.2014.0347
16. Gonsales, R., Vuds, R., Eddins, S. (2006). Tsifrovaya obrabotka izobrazheniy v srede Matlab. Moscow: Tekhnosfera, 616.Available at: https://en.sng1lib.org/book/2075428/0968c1