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INCREASING THE RELIABILITY OF DIAGNOSIS OF DIABETIC RETINOPATHY BASED ON MACHINE LEARNING

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This paper discusses the method of measuring and analyzing the parameters of the retina with subsequent diagnosis based on them of pathological changes due to diabetic retinopathy, which is crucial in the field of medicine to help doctors in timely detection and treatment of the disease. The main problem of biomedical image data analysis is insufficient pre-processing of images for further clear determination of informative indicators. This paper explores the application of machine learning and image processing techniques to develop an effective method for the diagnosis of diabetic retinopathy. The main focus is on obtaining the optimal model using machine learning and different types of neural networks. This paper considered and analyzed such methods of image preprocessing as: median filtering, grayscale conversion, cropping of non-informative areas of the image, selection of contours. The classification results of three rules (Classical Neural Networks (CNNs), Deep Neural Networks (DNNs) and Convolutional Neural Networks (CNNs) were analyzed, and through experimental studies it was determined that the ANN performed the task best (accuracy=87.1 %, reliability=84.6 %, sensitivity=91.6 %, specificity=84 %). An information model was obtained to support decision-making in assessing the condition of the retina using the processing of the obtained microscopic images and further analysis of informative parameters, and a database of more than 35,000 samples and informative features of the retina was formed. Given the sufficient quality of classification and the availability of software and hardware, this method can be developed and applied in practice in medical institutions after conducting all the necessary clinical studies

Keywords: fundus images, diabetic retinopathy, neural network, image preprocessing, medical image analysis

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1. Introduction

The world is witnessing a growing pandemic of diabetes, ranking among the most prevalent chronic conditions worldwide. According to the World Health Organization, at the beginning of 2020, more than 420 million people worldwide suffered from this disease [1]. Diabetes can lead to a number of serious complications, in particular, diabetic retinopathy, which occurs in patients with diabetes and can lead to vision loss [2].

According to the International Diabetes Federation, 537 million adults in the world live with diabetes, one in 10 suffer from this disease. According to forecasts, by 2030 their number may increase to 643 million or even 700 million [3, 4]. Diabetes can lead to problems with the retina, heart, kidneys and nerves. Diabetic retinopathy (DR) stands as a leading cause of blindness in developed nations [5–7].

This is a serious disease of the fundus that occurs because of diabetes. DR can damage the blood vessels in the eyes, which can lead to vision loss [2]. Diabetic retinopathy is the cause of blindness for 2.6 % of blind people [8]. Blindness in patients with diabetes occurs 25 times more often than in the general population. It is necessary to develop effective methods of treatment and prevention of DR to preserve vision in patients with diabetes. Visual disability is observed in more than 10 % of patients with diabetes.

Classification according to WHO [1]:

– nonproliferative retinopathy without maculopathy (mild – only microaneurysms, moderate and severe – with small hemorrhages and/or segmentally dilated retinal veins);

– nonproliferative retinopathy with maculopathy (mild maculopathy – changes distant from the center of the macula, moderate and severe – changes in the center of the macula);

– preproliferative retinopathy (intraretinal microvascular abnormalities);

– proliferative retinopathy;

– proliferative retinopathy with complications.

It is worth noting that the state of the art shows significant improvement and development due to the addition of a method for the analysis and processing of biomedical images, followed by the comparison of the obtained classification results for the selection of the best decision-making rule.

In this regard, the development of a method for the diagnosis of diabetic retinopathy is an important task in the medical field. Such a method can greatly facilitate the diagnostic process and help doctors detect and treat diabetic retinopathy in time [9].

The application of machine learning and image processing methods can become a powerful tool in the development of such method [10]. Machine learning, as a subset of artificial intelligence, focuses on the creation of algorithms and models capable of learning from data and making predictions when presented with new data. Image processing includes a number of methods that allow you to process and analyze images for the purpose of detecting diseases and complications.

Recently, research in the field of classification of diabetic retinopathy has become widespread due to open databases of retinal images, such as Kaggle [11], DDR [12], Messidor [13] and many others. In our opinion, Kaggle is the best for research because it contains more than 88,000 retina images of different sizes, taken by different owners and labeled accordingly.

Therefore, studies on the development of a method for the early diagnosis of diabetic retinopathy are scientifically relevant.

2. Literature review and problem statement

The research [14] is devoted to the diagnosis of such diseases as diabetic retinopathy, retinal vein occlusion, and age-related macular degeneration. This work involves a dataset of 15,089 CFPs obtained from 8,110 patients who underwent fundus fluorescein angiography (FFA) examinations. The main focus is on evaluating the models' ability to achieve precise diagnoses solely based on CFPs. The models, based on CNN architectures such as ResNet101, EfficientNetV2-M, and ConvNeXt-base, are augmented with an attention mechanism to highlight specific regions in fundus images. The advantage of this study is a fairly clear classification division into different types of diseases, which will help determine the correct diagnosis, and therefore timely treatment. In this work, no special pre-processing of the images was performed, but due to the method of fluorescence angiography, the classification showed a fairly high result. The disadvantage of the considered method is the invasiveness of the study.

The paper [15] proposed 18 pre-trained models based on the model structure and F1-score on the ImageNet dataset. The shortcoming of this work is the assessment of classification based on only one F1 parameter and insufficient pre-processing of images in case of noise.

The following work [16] is devoted to the development, investigation and identification of architectures and algorithms that relatively improve the detection of DR. In this study [16], unlike the previous ones, the image database was balanced, and pre-processing of the images, such as a Gaussian blur filter to reduce noise, was also performed. Experiments were conducted with two different deep learning (DL) models: a hybrid model based on a combination of VGG16 and XGBoost classifier and a DenseNet 121 model. The accuracy of these systems reached above 90 %. The main advantages of this work are the use of mixed types of neural network architectures, as well as the verification of a large number of decision rules. In this study, only one indicator is used to assess the quality of the classification.

The study [17] analyzes the opportunity of early detection and diagnosis of diabetes-related diseases, it uses the UCI (University of California Irvine) diabetic retinopathy dataset. The features for this dataset were taken from 1151 stock photos of patients in the open MESSIDOR database. The advantage of this work is the use of modern neural network algorithms to improve the quality of classification. This work also lacks image processing and uses an insufficiently large, unbalanced image database.

In the follow-up paper [18], the researchers went further, by analyzing the progression of diabetic retinopathy on retinal images, they developed and tested a deep learning system (DeepDR Plus) to predict the time to progression of DR over 5 years. The strength of this work is that considerable attention was paid to the pre-processing of images to extract informative indicators. This paper represents a significant contribution to the understanding of how deep learning can be used to predict the progression of diabetic retinopathy. Insufficient attention was paid to the preprocessing of the images to more accurately assess the current state of the patient's retina.

Studies [19, 20] have reviewed methods for detecting diabetic retinopathy based on neural network technologies. The strengths of the works are attempts to pay attention to a part of the image, as well as the use of various methods of changing the image database, by rotating them, etc., and much attention is also paid to the classification of diabetic retinopathy according to the stages of the disease. The authors also do not specify obvious approaches to improving images by means of preprocessing, so the results can be further improved using these methods.

So, after considering the works of many authors, as well as getting acquainted with the big problem of the spread of diabetes, and therefore other diseases related to it. There is a need to improve the methods of early diagnosis of diabetic retinopathy, which will reduce the negative impact on human vision, by combining image preprocessing (noise removal, cropping non-informative parts of the image, dimensionality reduction to reduce computing resources) and analysis. Informative characteristics were obtained with the help of neural network technologies. All this allows us to assert the expediency of conducting a study devoted to increasing the reliability of diagnosing diabetic retinopathy in the early stages.

3. The aim and objectives of the study

The aim of the study is to increase the reliability of diagnosing diabetic retinopathy in the early stages by using a decision support system based on the rules of neural network technologies.

To achieve this aim, the following objectives are accomplished:

– to develop image processing methods and algorithms for diagnosing diabetic retinopathy;

– to develop the architecture of the method;

– to conduct an experimental study of the developed method and compare the results with existing systems for the diagnosis of diabetic retinopathy;

– to assess the reliability (accuracy) of the retinopathy diagnostic method.

4. Materials and methods

The object of the study is the process of measuring and analyzing the parameters of the retina with subsequent diagnosis based on them of pathological changes due to diabetic retinopathy.

For the purpose of the research constructed in this way, the following hypothesis was formulated:

"According to the results of numerous laboratory studies, it is possible to build an information system for the diagnosis of diseases of the fundus, which allows the application of diabetic retinopathy even in the early stages with an accuracy of at least 80 %."

The main assumption is that paying a lot of attention to image processing with noise removal will increase informativeness for characteristic features of one or another category.

The simplifications given in this work consist in the omission of well-known methods of training neural networks.

The proposed method consists in automating the process of diagnosing diabetic retinopathy due to the automatic fixation of retinal images followed by pre-processing of the obtained images by combining known methods and training neural networks based on the obtained informative indicators.

A dataset of retina images [11] from kaggle.com was used, these data are freely available and contain more than 35126 training images and 15580 testing images. The dataset presents a challenge due to variations in image resolution and the presence of noise. To ensure accuracy and reliability, it is essential to apply appropriate filtering techniques to obtain a corrected dataset.

It is worth noting that a very important stage in the preparation and construction of an informational automated decision support system is the correct selection of informative parameters and image processing for analysis.

Initially, in order to distinguish a separate class of informative features, as well as to reduce the influence of different types of equipment and lighting on the result, the initial images were converted to grayscale.

One of these steps is to remove noise from the images to improve the selection of informative features of this or that diagnostic group.

The paper employs a median filter, a non-linear digital filtering technique utilized to eliminate noise and enhance overall results. This method offers advantages as it can preserve edges while effectively reducing noise, particularly under specific conditions.

The fundamental concept behind a median filter involves processing the signal from one record in conjunction with another, substituting each record with the median value of its neighboring records. In cases where a window (i. e., a set of neighboring samples) contains an odd number of entries, the median is the middle value when all entries in the window are sorted numerically. However, with an even number of entries, there may be more than one possible median value.

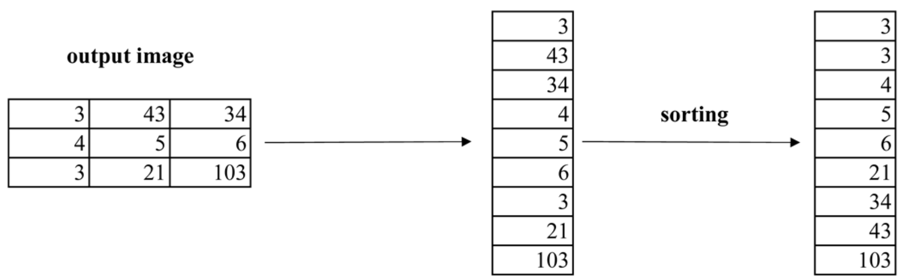


Fig. 1. The median filter

The median filter (Fig. 1, 2) proves to be a practical approach for processing information, particularly in the case of noisy images. It can adapt to matrices of various sizes, and unlike convolution matrices, the matrix size solely impacts the number of pixels taken into account.

The essence of the median filter is to select the median from a set of neighborhood pixels:

$$m_{i,j} = med\left[\mathrm{Im}_{i+s,j+t};(s,t \in W)\right]; i,j \in Z^2.$$

First, all neighborhood pixel values are sorted in a certain order (ascending) and the median value is selected to replace the central pixel (Fig. 3).

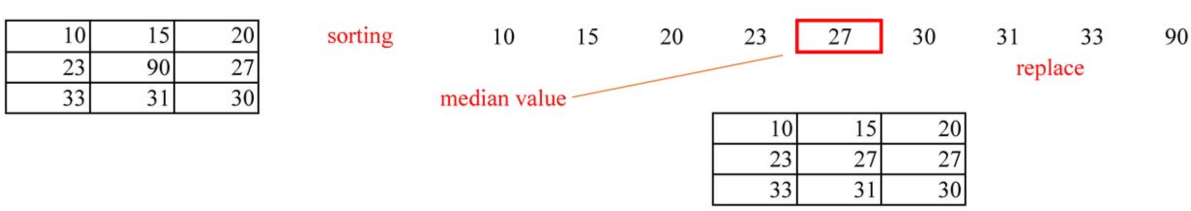


Fig. 2. An example of replacing the distinguishing value of a pixel

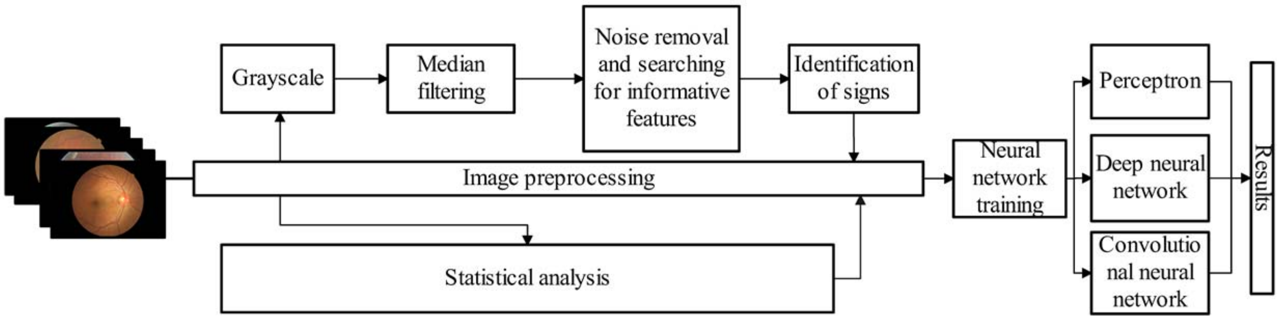


Fig. 3. Algorithm of the method of diabetic retinopathy analysis

Also, to facilitate work with data, it is worth cutting off non-informative parts of images, such as black background outside the retina. This will help to save the computing power of the system, and also help to work more accurately with the informative indicators of the images for different nosologies. Since we have a fairly significant amount of researched data.

The program requires input data in the form of images. These images were generated and reproduced using the experimental module for image processing, the architecture of which is depicted in Fig. 8.

These findings can contribute to improving the quality of diagnosis and classification of diseases, allowing for early detection and treatment. The development of a method incorporating machine learning and image processing techniques can greatly enhance the diagnostic process for diabetic retinopathy.

To generate informative metrics for training the decision support system, a set of statistical calculations was conducted on the processed images. These calculations included: Average value, Median, Standard deviation, Asymmetry, Mean squared error, Mean absolute deviation, Quartiles, Maximum, Minimum, and Threshold.

Fig. 3 shows a generalized method of diabetic retinopathy analysis. This image is a schematic of the image processing and neural network training process.

Here's more about each stage.

Grayscale conversion is a method that reduces the number of colors in an image to a single channel corresponding to the brightness of the pixels. This simplifies further image processing and reduces the amount of data.

The median filter is a method used to smooth the image and remove small noises. It works in such a way that for each pixel the average brightness value is chosen from its neighbors in a certain radius.

Noise removal and informative feature detection are techniques used to improve image quality and highlight important details such as contours, corners, textures, etc. These features can be useful for recognizing objects in an image or for classifying images according to certain criteria.

Statistical analysis is a method used to determine image characteristics such as mean, variance, entropy, histogram, etc. These characteristics can be used to compare images with each other or to detect anomalies or changes in the image.

Feature identification is a method used to extract certain features from an image that may be informative for a specific task. For example, to study eye diseases, it is possible to identify signs such as microaneurysms, hemorrhages, exudates, swellings, etc., which indicate the state of the retina.

Neural network training is a process used to create a model that can perform a specific function based on input data. A neural network consists of a large number of artificial neurons that are interconnected and can learn from data. In this study, three types of neural networks are used: Perceptron, Deep Neural Network and Convolutional Neural Network.

The next stage is the analysis of the obtained results to choose the best decision support system rule.

The essence of the method of early diagnosis of diabetic retinopathy is to increase the informative indicators, as well as to compare the diagnostic results obtained using a decision support system based on different rules.

To train a neural network based on the rule of a multilayer perceptron and a deep neural network from the initial processed images, statistical indicators are calculated, some of them are shown in (1).

Some formulas for calculating image statistics are given below (1):

$$M_1=\frac{1}{N}\sum_{k=1}^{N}\left(|x|\right)_k;\quad M_2=\sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(|x^2|\right)_k};$$

$$M_3\frac{1}{M_2^3}\frac{1}{N}\sum_{k=1}^{N}\left(|x^3|\right)_k;\quad M_4=\frac{1}{M_2^4}\frac{1}{N}\sum_{k=1}^{N}\left(|x^4|\right)_k, \tag{1}$$

where N is the number of elements of the orientation map;

x is the value of the pixel intensity of the k-th pixel of the image;

M_1–M_4 – statistical parameters (mean, variance, asymmetry, kurtosis).

The first-order statistical moment describes the average value of the coordinate distributions of the measured values. The second-order moment represents data dispersion, indicating the deviation from the mathematical expectation of the values. The third-order statistical moment quantifies the deviation from a normal distribution in the analyzed data. Finally, the fourth-order moment measures the magnitude of the "peak" in the distribution of matrix elements.

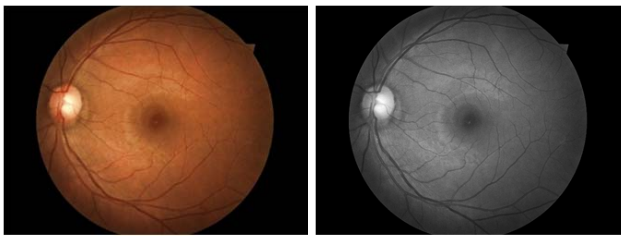
5. Research results of increasing the reliability of diagnosing diabetic retinopathy in the early stages by using a decision support system

5. 1. Developing image processing methods and algorithms for diagnosing diabetic retinopathy

In order to improve the selection of informative features, noise removal is an important step in the preparation and construction of an automated decision support system. Image pre-processing, including grayscale conversion and median filtering, is conducted to improve the accuracy of subsequent steps. Grayscale conversion simplifies the analysis of image characteristics, while the median filter removes noise while preserving edges.

Pre-processing of the image begins with the conversion of the given characteristics of the image into a grayscale for further analysis. The image classification process involves categorizing images based on the specified features, enabling the attainment of the desired outcomes (Fig. 4).

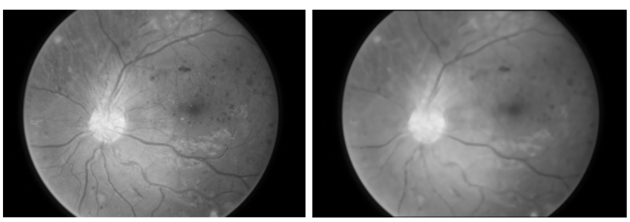
The use of the median filter is advantageous for processing noisy images, as it works with matrices of different sizes. In this study, the median filter effectively removes noise from the images.



a *b*

Fig. 4. Grayscale conversion:
a — input image; *b* — output image

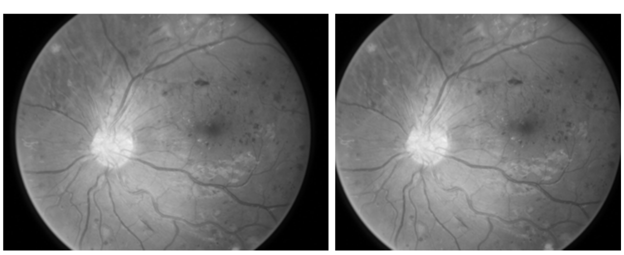
The Fig. 5 shows an example of the results of the median filter, which does an excellent job of removing noise.



a *b*

Fig. 5. Median filter performance results:
a — before filtration; *b* — after filtration

Additionally, non-informative parts of the images, such as the black background outside the retina, are cropped to save computing power and improve accuracy in analyzing the informative indicators of the images for different conditions (Fig. 6).



a *b*

Fig. 6. Cropping the image:
a — input image; *b* — output image of human retina

The input data for the program are images produced through an experimental module, the architecture of which is shown in Fig. 8. Examples of fundus images, images after preprocessing, are provided. These preprocessed images will be used to train the decision support system.

An example of fundus images, images after preprocessing, their 2-D and 3-D distribution histograms are shown in Fig. 7.

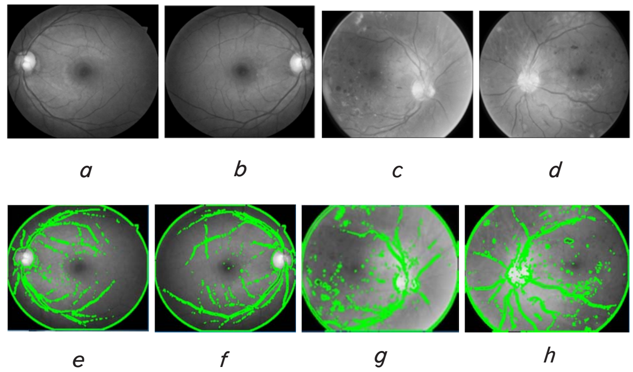


Fig. 7. An example of images: *a, b* — healthy retina; *c, d* — diseased retina after processing; *e, f* — images of healthy retina with selected characteristic features; *g, h* — images of diseased retina with selected characteristic features

To obtain information indicators for training the system, statistical calculations such as average value, median, standard deviation, asymmetry, mean squared error, mean absolute deviation, quartiles, maximum, minimum, and threshold are performed on the preprocessed images.

5. 2. Developing the architecture of the method of diabetic retinopathy early diagnostic

The architecture of the module for processing and analyzing images (Fig. 8) was developed, which allows for qualitative early diagnosis of diabetic retinopathy. The module includes the following main blocks: image database formation block, block of reproduction of the biological layer, analysis block, which made it possible to get closer to the practical use of the method in medical institutions.

Fig. 8 illustrates the comprehensive algorithmic and software architecture of the module dedicated to processing and analyzing images. It encompasses the following key components and modules:

– image capture module, a unit that receives images from a camera and converts them into a digital format;

– image saving module, a unit that stores images in the computer's memory or on external media;

– the module for forming micro commands for the unit of automatic control of system operation;

– a unit for determining the images;

– a unit for reproducing the parameters of the images, a unit that creates a structured database from processed retinal images. It uses such methods as histograms, grayscale conversion, reproduction of the biological layer, etc.;

– an analysis unit for determining informative features of coordinate distributions of two-dimensional images, a unit that performs statistical and direct analysis of images to identify characteristic signs of retinal diseases, such as microaneurysms, hemorrhages, exudates, edema, etc.;

– user interface module to facilitate operation and system management;

– block of the decision support system.

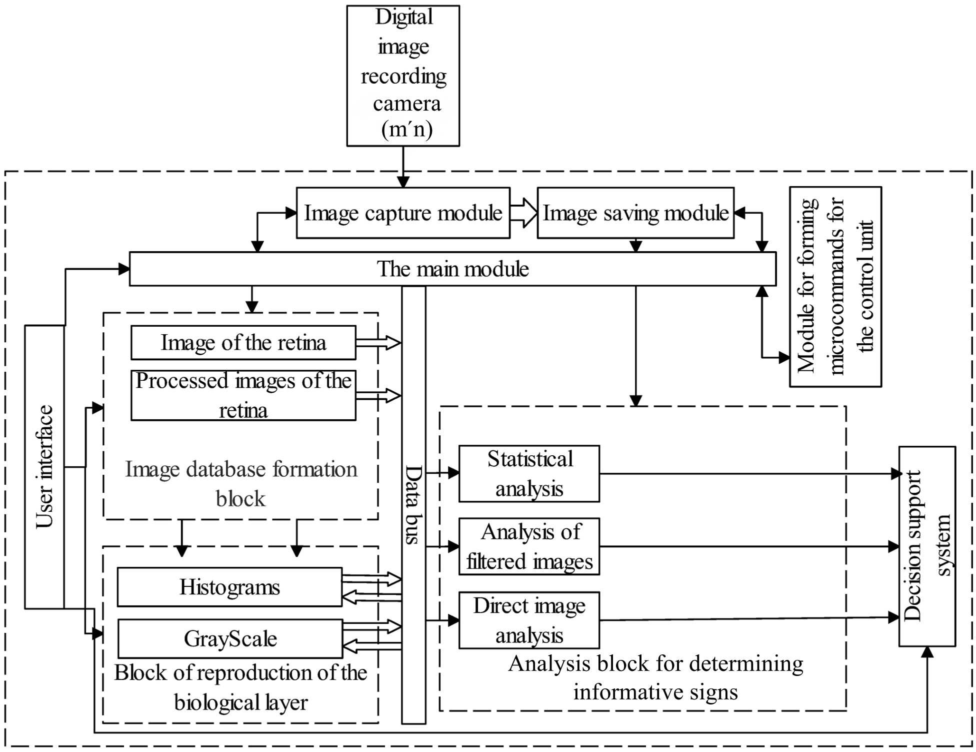


Fig. 8. Software architecture of the module designed for processing and analyzing images

The dataset used in this study is a FUNDUS image of the human retina with a pixel size of over 2,000×3,000. The dataset was downloaded from kaggle.com and contains more than 35,000 training images and 15,000 testing images. However, the dataset has varying resolutions and contains noise, so proper filtering is required to obtain the correct dataset.

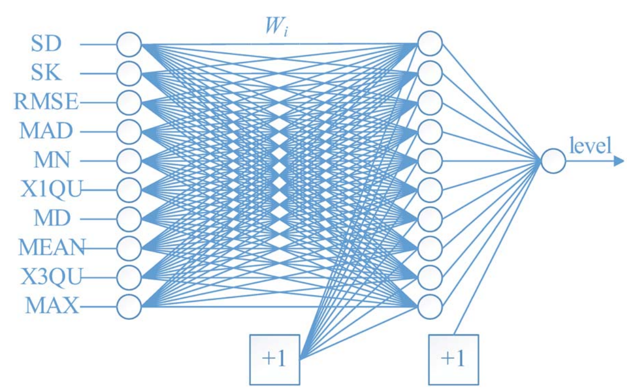
5. 3. Conducting an experimental study of the developed method of early diagnostic

Two neural networks, a perceptron-type neural network and a deep neural network, are tested and compared to improve the method. The trained diagnostic method is then tested using data that was not included in the training process. The Confusion Matrix is used to evaluate the quality of the classification model and identify errors.

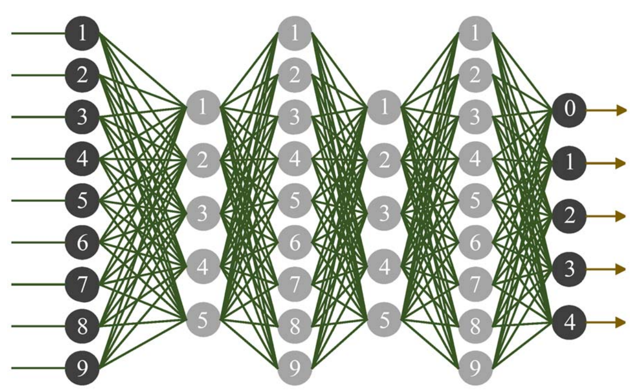
A convolutional neural network, which analyzes the direction of the image, is also used to compare and select the best rule. The image data were pre-processed using various methods, including shading of non-informative areas of the image, filtering to avoid errors associated with image noise and due to the fact that the obtained fundus images were taken using different equipment under different lighting conditions and under different conditions. morphological processing, determination of informative indicators and binary conversion (this technique shows significantly better results in comparison with unprocessed images of the fundus).

The implementation of the method was based on free open software in the Python programming language, the following libraries were used for analysis, data processing and training of neural networks: OpenCV, NumPy, Pandas, TensorFlow and Keras. All calculations were performed using a PC with Intel Core i5-13400F, NVIDIA GeForce RTX 3060, 16 GB RAM.

To compare and improve the method, it was decided to test two neural networks: a perceptron-type neural network (Fig. 9, *a*) and a deep neural network (Fig. 9, *b*).



a



b

Fig. 9. Two types of neural networks used: *a* – perceptron-type neural network model; *b* – deep neural network

Fig. 10 shows confusion matrixes, which are built based on the results of the studied algorithms. It is worth noting that the test sample of the investigated images is quite weighted, that is, the number of samples with “Normal” and “Pathology” is comparable.

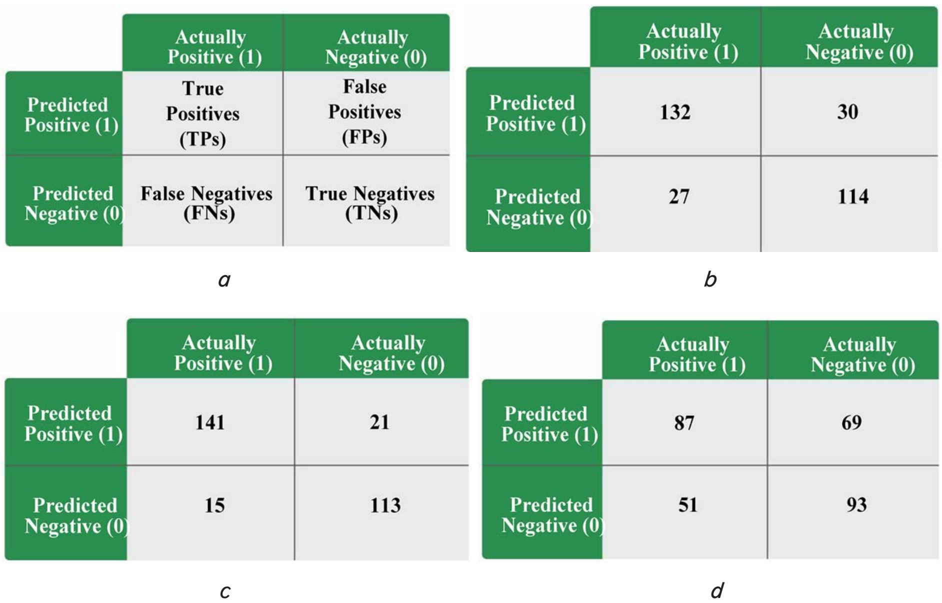


Fig. 10. Confusion Matrix: *a* — explanation; *b* — convolutional neural network; *c* — deep neural network; *d* — classical neural network

After the diagnostic system is trained on the training data, it is tested using the data that was excluded from the training process. Thus, it is possible to compare the predictions of the trained model with the actual values. The Confusion Matrix is a means of assessing the quality of the classification model and the location of errors (Fig. 10).

5. 4. Checking the reliability of the classification of the considered image analysis method

To assess the reliability of the classification of the considered image analysis method, we will use the classic characteristics of the informativeness of diagnostic medical systems [21]: Accuracy, Precision, Recall, and Specificity (2)–(5):

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} 100\,\%, \tag{2}$$

$$PRE = \frac{TP}{TP + FP} 100\,\%, \tag{3}$$

$$REC = \frac{TP}{TN + FN} 100\,\%, \tag{4}$$

$$SP = \frac{TN}{TN + FN} 100\,\%, \tag{5}$$

where Acc – accuracy;

PRE – precision;

REC – recall;

SP – specificity;

TP – true positive results;

TN – true negative results;

FP – false positive results;

FN – false negative results.

Digital indicators of the diagnostic system are given in Table 1.

Based on the provided Table 1 assessing the classification quality of different models on both training and testing datasets, we can draw the following conclusions: The deep neural network shows higher specificity compared to the perceptron and convolutional neural network, suggesting better performance in correctly identifying negative instances.

In summary, the deep neural network consistently outperforms the perceptron and convolutional neural network across various evaluation metrics, making it a more promising model for the given classification task.

As we can see according to Table 1, DNN showed the best classification results.

The high quality of classification is also proven by Fig. 11, which shows three ROC curves for the studied classification systems.

Table 1

Assessment of classification quality

Type of neural network	Accuracy		Precision		Recall		Specificity	
	Training dataset	Testing dataset	Training dataset	Testing dataset	Training dataset	Testing dataset	Training dataset	Testing dataset
Perceptron	60	61.2	46	55.7	64	63.4	57	57.1
Deep neural network	90.1	87.7	92	84.6	88.4	91.6	91.6	84
Convolutional neural network	83.3	81.1	83	81.4	85.9	83	80.3	79.1

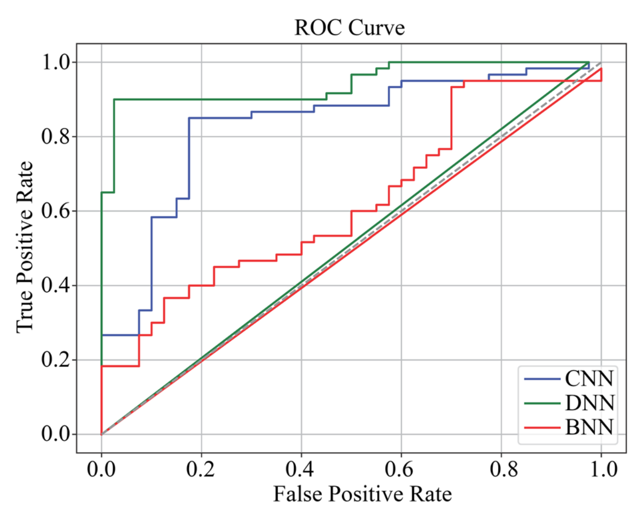


Fig. 11. Receiver operating characteristic curves of Classical Neural Network, Deep Neural Network and Convolutional Neural Network

In the proposed method for the early diagnosis of diabetic retinopathy, after comparing the decision rules, it was decided to focus on the combination and development of two decision support systems based on a deep neural network and a convolutional neural network. It is worth noting that both the calculated statistical parameters of retinal images and the images themselves after the pre-processing described in the previous sections served as input data for deep neural network training. The convolutional neural network was trained only on processed retinal images.

Again, we can make sure that the results of DNN and CNN are quite close and under different conditions can show themselves at a sufficiently high level for medical classification of diagnoses.

6. Discussion of the results of the development of a method for early diagnosis of diabetic retinopathy based on machine learning

It is worth noting that the improvement of the classification quality of the early diagnosis method is associated with a thorough approach to the task of preprocessing input images, which allows for the formation of a higher quality database for further work with it.

The results obtained in this study are based on a careful approach to the pre-processing of the investigated images. Examples of preprocessing are: grayscale conversion (Fig. 4), median removal of noise (Fig. 5), cropping of non-informative areas of the image (Fig. 6), selection of non-informative indicators (Fig. 7) reducing the size of the image several times to save computing resources (10 times), and others.

Compared with the existing works [14–18], a thorough analysis of the features of fundus image processing in diabetic retinopathy was carried out and a balanced database of images and informative indicators was formed for further work on improving the existing method of early diagnosis.

It is worth noting certain limitations of this method:

– research results are based on specific data sets used to train and test models. It is important to note that the data selected may not fully reflect the variety of scenarios in the real world;

– the uneven distribution of classes in the data could have affected the results;

– metrics such as accuracy, sensitivity, specificity, and others do not always give a complete picture of the model's effectiveness. In the following studies, it is planned to consider other metrics for evaluating the method, such as Precision-recall curves, F1 scores, etc.

However, it is important to acknowledge the limitations accompanying this study. Model architecture, training parameters, and data heterogeneity may impact the robustness of the results. Additionally, variations in outcomes may occur when applying different datasets or model configurations.

The findings of this research hold promising real-world implications, particularly in the integration of the developed neural network models into clinical practice. The ability of the deep neural network to achieve high accuracy, sensitivity, and specificity underscores its potential utility in various diagnostic applications.

The successful deployment of these neural network models in clinical settings could revolutionize diagnostic procedures. For instance, the method could be seamlessly integrated into existing medical imaging workflows to aid in the rapid and accurate identification of medical conditions. Its high sensitivity could enhance early detection, leading to timely intervention and improved patient outcomes.

While the potential benefits are significant, the integration of neural network models into clinical practice necessitates addressing challenges such as ensuring interpretability, validation across diverse patient populations, and adherence to ethical standards regarding patient privacy and data security.

An important aspect and an opportunity for future improvement of the method is the use of an unbalanced image database, and some samples are mislabeled. Therefore, there is a need for additional analysis of fundus images.

In conclusion, the application of modern diagnostic approaches, particularly neural network models, presents a transformative opportunity in clinical practice. The integration of such advanced technologies has the potential to enhance diagnostic accuracy, streamline workflows, and ultimately improve patient outcomes, ushering in a new era of precision medicine.

According to Table 1, the deep neural network (DNN) showed the best classification results in terms of accuracy, recall, and specificity.

The obtained results can be used to solve the problem of improving the quality of diagnosis and classification of diseases with the possibility of early detection and treatment of the disease. In the further development of the research, it is planned to check the quality of the classification using other rules and methods. The plan for further work is to expand the capabilities of the existing method by creating a relational database that will be managed by a suitable database management system with remote query, modification and data management capabilities (MySQL, PostgreSQL, or others).

Possibilities of improving the diagnosis of diseases according to the stages of diabetic retinopathy are also considered. This will facilitate the work of diagnosticians.

It is worth noting that the studies were conducted on a specific data set, and although it is large enough, testing on a different data set or different hardware may lead to unexpected results. Therefore, there is a need to further study this method with the expansion of the database and check the quality of classification based on other types of neural networks.

The development of a single closed system is planned, which will allow to carry out the entire cycle of diagnostics: from obtaining images, their processing, to the final diagnosis and treatment recommendations.

7. Conclusions

1. A method of image preprocessing was developed, which includes a combination of such approaches as: converting an image to grayscale, removing noise with the help of a median filter, extracting informative features, cropping non-informative areas of the image, reducing the size of the image several times to save computing resources (10 times).

2. The system architecture consisting of the following main blocks was developed: image database formation block, block of reproduction of the biological layer, analysis block. This development makes it possible to improve the quality of classification and verification of diagnoses without the

direct intervention of a doctor. The inclusion of a user interface in this system allows you to use it without complex preliminary settings and the involvement of relevant specialists.

3. Experimental research was conducted on learning a decision support system based on neural networks and further testing the resulting systems for choosing a decision rule. The research focused on assessing the classification quality using various neural network models has yielded crucial insights with significant implications for the contemporary fields of machine learning and data analysis. In the context of training and testing models on the specified datasets, the deep neural network exhibited remarkable effectiveness, delivering the highest metrics in terms of accuracy (87.7 %), sensitivity (91.6 %), and specificity (84 %). Its high accuracy and ability to correctly classify (84.6 %) both positive and negative instances underscore the substantial potential of this architecture for diverse classification tasks.

4. The classification quality was also checked and compared with other studies, which showed a fairly high result. The assessment was based on classical characteristics (Accuracy=87.7 %, Precision=84.6 %, Recall=91.6 %, Specificity=84 %). A decision support system based on neural networks was developed to help doctors in the process of diagnosing diseases of the fundus. The results of classification by three rules (BNN, DNN, CNN) were analyzed, their indicators were determined, and it was decided that DNN coped best with the task.

Conflicts of interest

The authors declare that they have no conflict of interest to report regarding the present study.

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Data availability

Data will be made available on reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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