System for neural network recognition of malignant pigmented skin neoplasms with image pre-processing

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Abstract. The article presents a system for the recognition of malignant pigmented skin neoplasms with a preliminary processing stage. Image pre-processing consists of removing hair structures from images, as well as resizing images and their further augmentation. Augmentation made it possible to increase the variety of training data, balance the number of images in different categories, and avoid retraining the neural network. The modeling was carried out using the MatLab R2020b software package for solving technical calculations on clinical dermatoscopic images from the international open archive ISIC Melanoma Project. The proposed system for the recognition of malignant pigmented skin neoplasms made it possible to increase the accuracy of image classification up to 80.55%. The use of the proposed recognition system will make it possible to increase the efficiency and quality of diagnosis, in comparison with the methods of visual diagnosis.

1. Introduction

Today cancer can be considered as one of the main causes of death in humans [1]. Skin cancer is one of the most common types of malignant lesions in the body [2-4]. Rapid and highly accurate diagnosis of skin cancer can reduce the risk of death among patients. Dermatoscopy is the most common visual diagnosis method. This method can be effectively used only by qualified specialists since it is based on visual acuity and the experience of a practicing physician [5]. Visual diagnosis of cancer-positive lesions at an early stage is difficult due to similar manifestations of benign and malignant skin neoplasms [6]. An expert dermatologist can achieve an average accuracy of 65% to 75% with dermatoscopy [7, 8].

Currently, medicine is considered one of the promising areas for the effective implementation of artificial intelligence, since the visual analysis of medical images is the most common method of research and diagnosis in this area. The creation of systems based on artificial intelligence will increase the efficiency and speed of diagnosis, and will also allow starting treatment at an earlier stage [9]. In [10], the authors presented an automated system for the classification of skin lesions based on deep neural networks, which made it possible to achieve an accuracy of 66.70%. The article [11] presents a skin cancer recognition system with the method of artificially increasing the number of images. The proposed method made it possible to classify images into two categories with an accuracy...
of 71.00%. In [12], the authors trained the convolutional neural network GoogleNet Inception v3. The accuracy of training when dividing the database into three categories was 72.10 ± 0.90%.

The main problem in the use of artificial intelligence in the field of dermatology is the low level of accuracy of recognition and classification systems. One of the possible ways to increase this indicator is the use of image preprocessing methods. When using automated diagnostic systems, the presence of noise distortions, for example, hair, can dramatically change the size, shape, color, and texture of the lesion, which greatly affects the analysis result. Removing hair from images at the pre-processing stage is an important step in the development of automated diagnostic systems [13]. Another important problem when creating systems for automated recognition of medical images is the limited amount of available data for training neural network systems. The use of augmentation methods as a stage of data preprocessing makes it possible to increase the amount of training data and prevent the problem of retraining the neural network system [14].

The paper proposes a neural network classification system for pigmented skin neoplasms with a stage of preliminary image processing. This stage of preprocessing makes it possible to prepare dermatoscopic images for further analysis to carry out automated recognition of malignant skin lesions.

2. Method of morphological processing of images of pigmented skin lesions to remove hair structures

When examining pigmented lesions, the presence of hair in images can obscure important diagnostic information, thereby reducing the effectiveness and quality of examination results. Figure 1 shows an example of how the presence of hair structures can dramatically change the size, shape of the lesion, and the pattern on the texture of the image.

![Figure 1](image_url)

**Figure 1.** Examples of dermatoscopic images of skin lesions containing hair defects: a) benign; b) malignant.

The solution to this problem is the digital processing of dermatoscopic images with the replacement of hair structure pixels with skin pixels. The solution to this problem is the digital processing of dermatoscopic images with the replacement of hair structure pixels with skin pixels. To do this, it is necessary to identify each pixel of the image as a pixel-hair or pixel-skin and replace the pixel-hair with a pixel-skin with a further assessment of the preservation of diagnostic features [15]. One of the possible ways to identify and replace hair pixels is morphological image processing. The proposed method of morphological preprocessing of images of pigmented skin lesions consists of such basic steps as decomposition of an RGB image into color components; locating hair; replacing hair pixels with neighboring pixels; reverse construction of a color RGB dermatoscopic image.
Dermatoscopic RGB image \( D(x,y) \) is decomposed into color components \( D_R \), \( D_G \) and \( D_B \). Processing is performed separately for each color component. To carry out further morphological operations, it is necessary to enter the variables \( K_1 \) and \( K_2 \).

\[
K_{1,2} = \{(x,y): \rho(W,(x,y)) \leq r\},
\]

where \( \rho \) is the distance from the center \( W \) of the set \( K_{1,2} \) by the chosen metric; \( r \) is the radius of the set, specified by the user.

To identify the location of hair structures on the image, a morphological closure operation is performed with a \( K_1 \) element. This operation leads to a smoothing of the areas of the contours of the hair structures and fills in narrow gaps, as well as eliminates voids and fills in the contour gaps [16]. The next step is to subtract the original image \( D(x,y) \) from the one obtained as a result of the closing operation.

To carry out further morphological operations, it is necessary to introduce the operator of zeroing \( \gamma \) image pixels \( D(x,y) \):

\[
\gamma(D(x,y)) = \begin{cases} D(x,y), & \text{if } D(x,y) > N \\ 0, & \text{if } D(x,y) \leq N \end{cases},
\]

where \( N \) is the threshold of pixel intensity values, which is set by the user.

After identifying the location of the hair structures on the image, a threshold zeroing of pixels is performed by applying the introduced zeroing operator \( \gamma \) to the image \( D(x,y) \). To expand the boundaries of the hair structures, a morphological operation of dilation with the \( K_2 \) element is performed. Element \( K_2 \) defines the type and degree of thickening that is produced during the dilatation operation.

To replace the pixels of the hair structures with neighboring pixels, interpolation into the pixels from the border of the selected area is performed using the Laplace equation. In this case, the border pixels are not subject to change. To reverse build an RGB color image from the extracted color components, the color channels are combined.

3. Method of augmentation and transformation of the sizes of dermatoscopic images of pigmented skin lesions

As with any image classification task, the use of large amounts of training data provides significant performance gains for the skin lesion classification task. One of the main methods for augmentation of dermatoscopic images of pigmented skin lesions is affinity transformations in two-dimensional space, where each image is a plane. Rotation and flipping are one of the methods of affine transformations. Random rotation by a certain angle allows you to get a mirror image of the original image along the selected axis. The operation of rotation by an angle \( \varphi \) around the center of the image is as follows:

\[
\begin{pmatrix}
  x'_i \\
  y'_i 
\end{pmatrix} = \begin{pmatrix}
  \cos \varphi & -\sin \varphi \\
  \sin \varphi & \cos \varphi 
\end{pmatrix} \begin{pmatrix}
  x_i \\
  y_i 
\end{pmatrix},
\]

where \( (x_i, y_i), i \in I \), \( I \) is the set of all pixels.

The translation operation shifts the entire image by the specified number of pixels in the selected direction. This method allows the network to focus on spatially invariant objects.

Scaling and cropping allows rotating the original image \( D(x,y) \) indifferent directions using the scaling operator \( S \).

\[
S = \begin{pmatrix}
  s_q & 0 \\
  0 & s_z
\end{pmatrix},
\]

where \( s_q, s_z \) scaling factors for the \( q \) and \( z \) training set of directions, respectively. Since the database of images of dermatoscopic skin lesions consists of images of different sizes, scaling allows
transforming the data into a set of a single size. Since different neural network architectures require images of the same size, scaling is usually combined with cropping to obtain the required image sizes.

Shearing is the procedure that displaces each pixel in a fixed direction, by an amount proportional to its signed distance from the line that is parallel to that direction and goes through the origin. Let’s a shear parallel to the $x$ axis has $x' = x + ky$ and $y' = y$. Written in matrix form, this becomes

$$
\begin{pmatrix}
x' \\
y'
\end{pmatrix} = \begin{pmatrix} 1 & k \\ 0 & 1 \end{pmatrix} \begin{pmatrix} x \\
y
\end{pmatrix}.
$$

(5)

Analogically for shear parallel to the $x$ axis.

Augmentation consists of combining all the listed methods of increasing the number of training images. Let’s consider that affine transformation $T$ is the sum of rotations $T_1$, scalings $T_2$, translations $T_3$, squeezings $T_4$ and shearings $T_5$. Then $T$ can be written by

$$
T = \sum_{i=1}^{5} T_i.
$$

(6)

Then combined augmentation can be written as

$$
R(T) = R(\sum_{i=1}^{5} T_i) = \sum_{i=1}^{5} R(T_i) = \sum_{i=1}^{5} T_i(R) = T(R).
$$

(7)

Generating new data from existing data using augmentation allows you to increase the available volume of training images for more effective training. Augmentation allows you to transform original images in shape, size, position.

3. System for neural network recognition of malignant pigmented skin neoplasms

A convolutional neural network classifier was used to recognize dermatoscopic images of skin lesions. The neural network system for the determination of malignant skin lesions based on dermatoscopic images is shown in Figure 2.

Figure 2. System for neural network recognition of malignant pigmented skin neoplasms with preliminary image processing.

Convolutional neural network technologies are recognized as the most optimal for pattern recognition in the field of artificial intelligence [17]. The essence of convolutional neural networks is to alternately apply convolutional layers and sample layers. This type of neural network includes input and output layers, several hidden layers, represented by convolutional layers, selection layers, and a fully connected classifier. The neural network includes neurons with activation $\alpha$ and parameters $\theta = \{V, M\}$ where $V$ is the vector of weights, and $M$ is the vector of displacements. Activation is a linear combination of the input $j$ to the neuron and parameters, followed by a transfer function $\sigma$.

$$
\alpha = \sigma(V^T x + b).
$$

(8)

The most famous version of traditional neural networks is the multilayer perceptron, which has several levels of transformation:

$$
f(j, \theta) = \sigma(V^n \sigma(V^{n-1} \ldots \sigma(V^0j + b^0) \ldots + b^{n-1}) + b^n),
$$

(9)
where $V^m$ is a matrix consisting of rows $V_p$ connected at the output with activation $p$; $m$ is a number of the current layer; $n$ is the last layer.

4. Modeling a neural network classification system for dermatoscopic images of pigmented skin lesions

For modeling, clinical dermatoscopic images were selected from the international open archive ISIC Melanoma Project [18]. This archive is a database of digital representative images of all important diagnostic categories in the field of pigmented skin neoplasms. Images are presented in various sizes. A total of 32454 images were selected, which were divided into two diagnostic categories, such as benign (21939) and malignant (10515) skin lesions. For a qualitative assessment of the developed system of neural network determination of malignant skin lesions, training was carried out for various architectures of convolutional neural networks based on the formed base of images of skin lesions. The simulation was carried out using the MatLab R2020b software package for solving technical calculations. The calculations were performed on a PC with an Intel (R) Core (TM) i5-8500 CPU @ 3.00GHz with 16 GB of RAM and 64-bit operating system Windows 10.

To carry out pretreatment using morphological operations, an empirical analysis of the application of formula (1) showed that the best result of identification and cleaning of hair structures is achieved at $r = 5$ for the $K_1$ element and at $3 \leq r = 3$ for the $K_2$ element. The Euclidean norm ($L^2$) was used as a metric [19]. Examples of preliminary morphological processing of dermatoscopic images to remove hair structures are shown in Figure 3.

![Figure 3](image-url)

Figure 3. Examples of the method for identifying and cleaning hair from dermatoscopic images: a) initial dermatoscopic image b) final pre-processed image.

At the stage of augmentation, an arbitrary rotation by an angle of 20 degrees was performed, as well as horizontal and vertical displacement of images in the range [-3 3]. Examples of images that have passed the stage of affine transformations are shown in Figure 4.

![Figure 4](image-url)

Figure 4. Examples of dermatoscopic images that have passed the preprocessing stage using affine transformations.
For modeling, used the Darknet-19 [20], NASNetMobile [21], GoogLeNet [22], EfficientNet [23], MobileNet [24] architectures pre-trained on a set of natural images ImageNet [25]. The scaling size was set automatically by the requirements for the input images of the selected neural network architectures. For NASNetMobile, GoogLeNet, EfficientNet, and MobileNet architectures, the size of the input images was 224 by 224 pixels. For the Darknet-19 architecture, the size of the input images was 256 by 256 pixels. The results of assessing the accuracy of classification of dermatoscopic images of pigmented skin neoplasms are presented in Table 1. Figure 5-9 show matrices of errors in training selected neural network architectures and neural network recognition systems with a preprocessing stage.

**Table 1.** Results of modeling a neural network recognition system for malignant skin lesions.

| Neural network architecture | Original neural network architecture, % | The proposed system of neural network classification with pre-processing of images, % | Improving recognition accuracy, % |
|-----------------------------|----------------------------------------|-------------------------------------------------------------------------------------|----------------------------------|
| Darknet-19 [20]             | 65.73                                  | 67.71                                                                               | 1.98                             |
| NASNetMobile [21]           | 73.08                                  | 76.85                                                                               | 3.77                             |
| GoogLeNet [22]              | 79.14                                  | 80.21                                                                               | 1.07                             |
| EfficientNet [23]           | 78.03                                  | 80.38                                                                               | 2.25                             |
| MobileNet [24]              | **76.75**                              | **80.55**                                                                           | **3.80**                         |

**Figure 5.** Confusion matrix a result of training the a) Darknet-19 neural network [20] b) neural network system for recognition of malignant skin lesions with a stage of preliminary image processing with Darknet-19 architecture [20].

**Figure 6.** Confusion matrix a result of training the a) NASNetMobile neural network [21] b) neural network system for recognition of malignant skin lesions with a stage of preliminary image processing with NASNetMobile architecture [21].
The highest indicator of the accuracy of recognition of malignant pigmented skin lesions was achieved using a neural network classification system with a preliminary image processing stage with a pre-trained MobileNet architecture [24] and amounted to 80.55%. When training each neural network architecture using the stage of preliminary processing of dermatoscopic images, the obtained
percentage of recognition accuracy is higher than when training the original neural network architecture without the stage of preliminary processing. The increase in recognition accuracy when training neural network classification systems with an image preprocessing stage was 1.07-3.80%, depending on the architecture. The best indicator of improving the recognition accuracy was obtained when training a neural network classification system with a preprocessing stage with a pre-trained MobileNet architecture [24] and amounted to 3.80%. The modified GoogLeNet [22] showed the smallest result of increasing the recognition accuracy by 1.07%.

7. Conclusion
The article presents a system for neural network recognition of dermatoscopic images of pigmented skin lesions. Modeling the proposed system made it possible to achieve a recognition accuracy of 80.55%. Application of the proposed stage of preliminary processing of dermatoscopic images allows increasing the recognition accuracy by 0.60-3.17%, depending on the architecture. The use of the proposed preprocessing stage for recognition and classification systems for dermatoscopic images of pigmented lesions can improve the quality of recognition in neural network classification systems.

The resulting indicator is superior to the results presented in the studies reviewed. The proposed system showed more effective results in comparison with visual diagnostics of specialist dermatologists using dermatoscopy. The use of the proposed system for the recognition of malignant lesions will allow dermatologists to increase the accuracy and efficiency in comparison with the methods of visual diagnostics.

A promising direction for further research is the construction of more complex systems for neural network classification of pigmented skin neoplasms, using, along with the analysis of the image of the neoplasm, various metadata about patients, such as age, gender, race, genetic predisposition.

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