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MULTICLASS SKIN LESSIONS CLASSIFICATION BASED ON DEEP NEURAL NETWORKS

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Abstract. *Skin diseases diagnosed with dermatoscopy are becoming more and more common. The use of computerized diagnostic systems becomes extremely effective. Non-invasive methods of diagnostics, such as deep neural networks, are an increasingly common tool studied by scientists. The article presents an overview of selected main issues related to the multi-class classification process: the stage of database selection, initial image processing, selection of the learning data set, classification tools, network training stage and obtaining final results. The described actions were implemented using available deep neural networks. The article pay attention to the final results of available models, such as effectiveness, specificity, classification accuracy for different numbers of classes and available data sets.*

Keywords: dermatoscopic images, multiclass classification, skin lesions, deep neural networks

WIELOKLASOWA KLASYFIKACJA ZNAMION SKÓRNYCH W OPARCIU O GŁĘBOKIE SIECI NEURONOWE

Streszczenie. *Choroby skóry diagnozowane za pomocą dermatoskopii są coraz powszechniejsze. Wykorzystanie skomputeryzowanych systemów diagnostyki staje się niezwykle skuteczne. Nieinwazyjne metody diagnostyki, jakimi są głębokie sieci neuronowe są coraz powszechniejszym narzędziem badanym przez naukowców. W artykule przedstawiono przegląd wybranych głównych zagadnień związanych w procesem klasyfikacji wieloklasowej: etap wyboru bazy danych, wstępnego przetwarzania obrazów, doboru zestawu danych uczących, narzędzi klasyfikacji, etapu trenowania sieci i otrzymania wyników końcowych. Opisane działania zostały zaimplementowane za pomocą dostępnych głębokich sieci neuronowych. W artykule zwrócono uwagę na wyniki końcowe dostępnych modeli, takich jak skuteczność, specyficzność, dokładność klasyfikacji dla różnej ilości klas i dostępnych zestawów danych.*

Słowa kluczowe: obrazy dermatoskopowe, wieloklasowa klasyfikacja, zmiany skórne, głębokie sieci neuronowe

Introduction

Skin cancers are often diagnosed dangerous skin diseases, including: squamous cell carcinoma, malignat melanoma, basal cell carcinoma and many others. Malignat melanoma is definitely the cancer with the highest growth dynamics, although it ranks 14th in terms of the number of cancer cases in Poland. In 2016, over 3,600 new cases and over 1,300 deaths were recorded in Poland [49]. However, the most commonly diagnosed benign birthmarks are: nevus, pigmented benign keratosis and seborrheic keratosis. The problem of diagnosing skin cancers is difficult, because it is often ignored by patients who come to the dermatologist too late to consult a skin lesion. Patients come to the doctor already with an advanced condition requiring specialized oncological treatment.

Dermatoscopy is a non-invasive imaging technique that allows you to make many, high-resolution images of skin birthmarks. Diagnostics based on images is currently very effective due to the use of algorithms based on artificial intelligence [7, 21, 24, 26]. The skin nevus diagnosed by the algorithm to confirm the diagnosis should be examined by a doctor. If the doctor's diagnosis is confirmed with the diagnosis of the diagnostic tool, the patient should undergo a histopathological examination.

Over the past decade, methods of automatic diagnosis of skin birthmarks from dermatoscopic images have gained great popularity [8, 23]. We owe the emergence of automatic methods to the machine learning development, the aim of which is to build a system capable of automatic improvement and acquisition of new skills based on the information provided. Widely used in non-invasive diagnostics of skin diseases find deep convolutional neural networks DCNN [10, 22, 31]. Deep learning has made it possible to diagnose many diseases through the use of a segmentation and classification process. Statistics indicate the greatest interest in the use of artificial neural networks in the process of segmentation. Increasingly, DCNN is used for this purpose to segment the region of interest, network training to classify dermatoscopic images [11, 48, 50].

Nowadays, it is the diagnostic methods based on these structures that develop the fastest. The most commonly implemented classification in earlier years was the binary classification [5, 16, 27]. The input data was divided into two classes, malignant melanoma versus no-melanoma or begin nevi. As the complexity of algorithms developed, deep neural networks developed, and more computational capabilities appeared in the classification of more classes. Currently developed models allow the classification of 5, 6 and even 7 different skin diseases [28, 29]. The use of more dermatoscopic images and more complex models of convolutional networks allowed to achieve great success in the diagnostic process [25, 43, 44]. Even papers are being created comparing the diagnostic capabilities of neural networks and dermatologists [13].

1. Database and preprocessing

Many works have been created using many generally available dermatoscopic databases. These databases contain images of skin lesions previously well diagnosed by doctors, making them a reliable basis for training the training of created neural network models. The most extensive and largest database is the ISIC database [20], which contains more than 20,000 dermatoscopic images of previously diagnosed skin lesions. MED-NODE database [30] contains 100 images of melanoma and 70 skin nevi. Among them should be mentioned the most famous: PH2 [34], PAD-UFES-20 [32], DERMOFIT [9]. Figure 1 shows examples of dermatoscopic images of six skin diseases from the most well-known and largest of the databases.

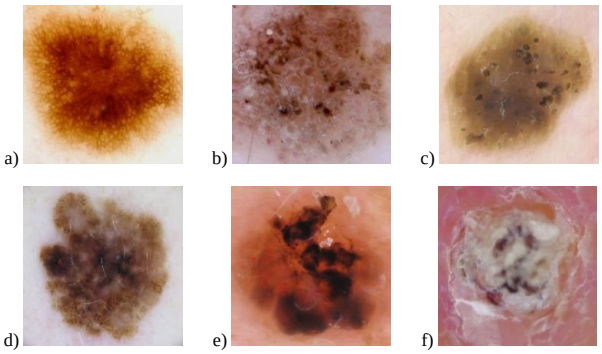


Fig. 1. Sample images of each class in ISIC: a) Nevus, b) Pigmented benign keratosis, c) Seborrheic keratosis, d) Malignant melanoma, e) Basal cell carcinoma, f) Squamous cell carcinoma [20]

Images of skin lesions taken from the database are subjected to a preliminary preparation process. In order to give images to the segmentation process, they should be well prepared. Images often contain artifacts such as medical tags, a scale applied to the skin, dark hair, air bubbles, blood vessels and skin lines. Automatic tools have been developed to remove artifacts from dermatoscopic images: edge filters, DullRazar. Artifacts in the images interfere with the process of identifying the skin lesion.

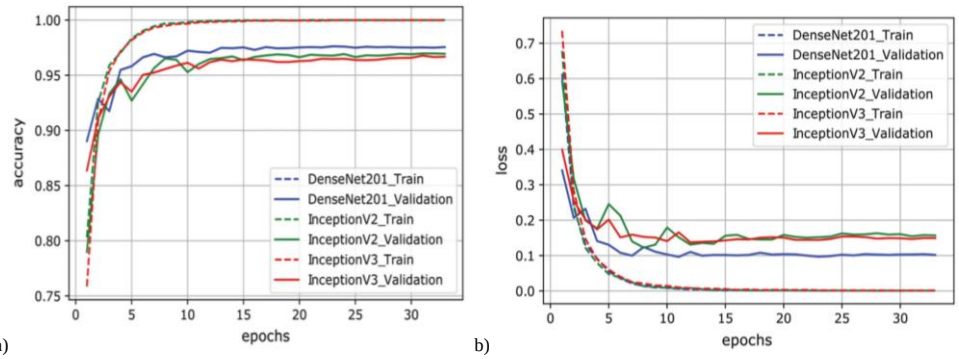
The next stage is to prepare an appropriate database of training and test images for a given class. Images previously diagnosed correctly by doctors based on a biopsy. Before the segmentation stage, areas of interest (ROI) are designated, which includes the skin lesion. Computer image analysis is used to monitor the boundaries of skin lesions. Currently, a number of automatic edge segmentation algorithms, active contours, K-medium, Otsu, fuzzy c-averages, "center split", "split and merge" and adaptive thresholding are used.

2. Training networks

Deep neural networks consist of multiple layers, each identifying more complex elements of the input image. For the created network, the input image of the skin lesion can be classified as an element of one of the defined classes. Deep neural networks consist of multiple layers, each identifying more complex elements of the input image. A convolutional network is a complex structure, which has the number of layers ranges from several dozen to several hundred. The subsequent steps that take place in each (parameterized by weights) layers transform the input data set into the output set.

Many neural network models have been created for image processing, including MobileNet [17], MobileNetV2 [40], DenseNet [18], NASNet, Xception, VGG16, VGG19, ResNet, InceptionV3, InceptionResNetV2 and many others. These models are very often used by researchers. The obtained samples are divided into three sets: training, validation and test. The created models are implent and the learning process takes place. Figure 2 shows a simplified diagram of the example architecture of the created DenseNet-201 network model, which was used in [43] to classify dermatoscopic images. It was created on the basis of the Keras library [33], which is used in transfer learning. In the network diagram there are blocks that contain fine-tuned layers (red), the non-modified (blue). The last of them are marked in purple the dense layers. Model has hidden layers and the ReLU function. Softmax is an activation function. DenseNet uses layer-to-layer connections, each previous layer is connected to the incoming layer. Also dense blocks, feature maps of all recent layers are combined with subsequent layers.

The entire network learning process is accompanied by skilful diagnostics of the model based on the created learning and validation curves. Based on the course of learning and validation charts, it is possible to determine whether there is undertraining, overtraining or matching in a given model. Depending on the implemented model, the training process gives a different effect. The assessment of the effectiveness of the model is made on the basis of the accuracy and loss value in relation to the number of epochs made through the network on the charts. Figure 3 shows evolution of accuracy and loss of the training and validation processes in [43]. After the process of training the network, the chart presented below should be obtained, the interpretation of these curves informs about the effect of the training method or about the selection of appropriate training data. The best results during training are achieved when the accuracy value tends closest to 1. After the process of training the network, the chart presented below should be obtained, the interpretation of these curves informs about the effect of the training method or about the selection of appropriate training data. It is important that the network is well trained, not overtrained, and that the data is matched to the model created.



a) b)

Fig. 3. Evolution of a) accuracy and b) loss of the training and validation [43]

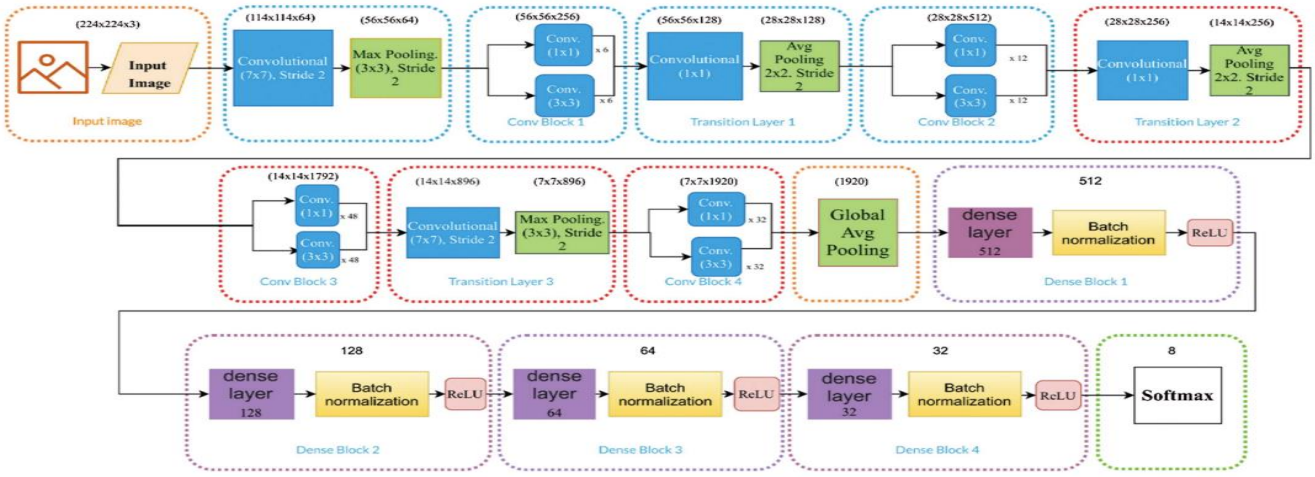


Fig. 2. DenseNet-201 model optimization [43]

The process of learning very large networks can be extremely time-consuming. An element that has a huge impact on the speed of learning is the appropriate the optimizer selection The optimizer is one of the essential elements of network models [1, 37]. Its task is to determine the course of network training. The loss function (which is a value minimized in the training process), it acts as a measure of the success of the task performed. Its task is to compare the results of network predictions with target labels. Based on them, he calculates the value of the loss. The optimizer uses them when modifying network weights, modifies networks based on the loss function. In [15] experiments were carried out to compare the results of the optimizers used and the linear rate (LR). Figure 4 shows the result for training and validation accuracy. Choosing the right LR value is not an easy task, which is why their values were analyzed. Adadelta, Adam, different LR scheduler schemes, Cyclical Learning Rates (CyLR) were studied. The most commonly used optimizers are momentum optimization, Nesterov algorithm, AdaGrad, RMSProp, Adam algorithm.

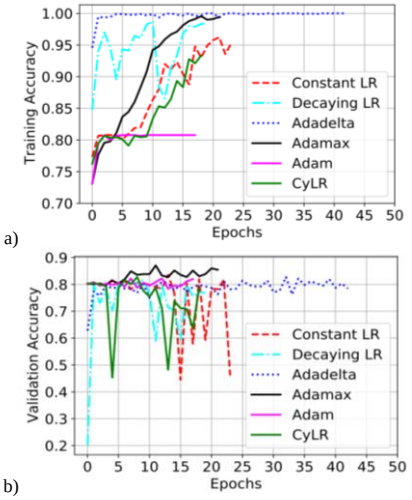


Fig. 4. The results for used optimizers and learning rate for: a) training accuracy, b) validation accuracy [15]

3. Lesions classification process

The emergence of new models of deep neural networks has increased interest in automated diagnostic processes for many diseases. Also the object of interest became the skin and skin birthmarks on it. Work on multi-class classification began to 3 classes, then expanding algorithms and increasing the computational capabilities of the created classification by 3, 5, 7 [7] and even 10 different classes. Classification can be based on a set of data divided into several classes. Deep neural networks allow you to diagnose even several skin diseases at the same time It all depends on how many samples we have. Extensive systems use images of different birthmarks, each of the diseases is marked as a class. The review of the multiclass classification was carried out in many works [2, 4, 21, 36, 38, 47]. Table 1 presents a list of works that achieved a high ACC score for the classification of skin birthmarks based on CNN. Many tools were used in the works, e.g. Generative Adversarial Network, fine-grained classification, augmenting labeled images, Combining Global–Local model. Combining them with a well-chosen network model and a representative database allowed to obtain high AUC values.

Over the years, scientists have focused on developing an algorithm to classify as many skin diseases as possible. [26] diagnosed 3 disease classes (SK, melanoma, and nevus) based on a database containing (training set) 2,000 and (test set) 150 images. The classification results are 76% sensitivity, 85% specificity and AUC 0.87. Of course, using as many images as possible also gives you more success. This was proven in [29] using more than 11,000 biopsyverified images to classify five (AK, intraepithelial carci-noma, benign keratosis, melanocytic nevi, and melanoma) and achieving a score of AUC = 0.96.

Table 1. Results for the segmentation and classification CNN's models in 2020 [38]

Study	Used model	Main details	Accuracy
[35]	ResNet50 GANs	data augmentation technique based on Generative Adversarial Network (GAN) ISIC 2018	95.2%
[45]	DC-MobileNetV1 DC-DenseNet121	Lightweight recognition model, discriminates features guided by fine-grained classification ISBI 2016	96%
[39]	MobileNet, VGG16 Custom model	classification augmenting labeled images, extracting features PH2	97.25%
[46]	LBP Resnet-50 DenseNet-121	Global–Local model, tailor-made features and deep Conv-features ISIC-2017	84.8 % for MM 91.3 % for SK
[3]	Inception-ResNet-v2	binary classification (benign and melanoma cases), integrated deep learning-based CAD system ISIC 2016	81.79%

Table 2. Results for the best algorithms in [42] for seven classes

Disease categories	Sensitivity	Specificity	Negative predictive value	Positive predictive value
Actinic keratoses and Bowen's disease	90.7%	98.5%	99.7%	62.9%
Basal cell carcinoma	88.4%	98.4%	99.2%	78.5%
Benign keratinocytic lesions	83.8%	98.3%	97.2%	89.3%
Dermatofibroma	81.8%	99.3%	99.5%	78.3%
Melanoma	81.9%	96.2%	97.6%	73.6%
Melanocytic nevus	91.6%	94.2%	88.3%	96.0%
Vascular lesions	89.2%	99.5%	99.7%	82.5%

The [7] MobileNet model was used based on multiple dermatosp images, and they were classified into seven selected classes, and the highest AUC score was over 0.95. Comparing the effects of different network models is one of the main activities of researchers. Classification also into 7 classes (actinic keratoses and Bowen's disease, basal cell carcinoma, benign keratinocytic lesions, dermatofibroma; melanoma; melanocytic nevi, vascular lesions were made in [32]. The paper compared the results of 139 models that were designed by 77 different teams. Table 2 shows the best results achieved for three algorithms when classifying seven different skin diseases diagnosed on images of skin lesions. The paper [42] analyzed the effectiveness of not only deep network models, but also doctors. An analysis was made for thirty selected dermatoscopic images, much better diagnostic results were achieved by selected neural networks than average human reader or even expert readers. The right number of diagnosed dermatoscopic images allows you to evaluate as many as 8 different classes [43].

In [14], the largest number of classes was diagnosed – 10disease (ne-vus, angio-ma/angiokeratoma, seborrheic keratosis, dermatofi-broma, solar lentigo, actinic keratoses, Bowen's disease, mela-noma, basal cell carcinoma and squamous cell carcinoma) based on imaging data from multiple databases. The degree of malignancy of lesions from begin to more malignat diseases was also estimated. The highest scores achieved were 95.0% sensitivity and 80.4% specificity for benign versus malignant. The process of network learning primarily takes place in the hidden network layer. Here, first of all, linear and nonlinear dependencies are sought. There can be multiple hidden layers. The more hidden layers a network has, the deeper dependencies it can find.

4. Testing networks

An appropriate dataset is also prepared for the network testing process. To assess the performance of classifiers, measures of the quality of the classifications carried out are used [12]. Performance metrics are used to assess effectiveness, one of which is the confusion matrix, where prediction results for individual classes are given. Figure 5 shows the confusion matrix it is characterized by the number of cases diagnosed as positive

and negative cases based on the real and predicted class. In the case considered in figure 5, the classification included seven classes with the highest probability of being diagnosed correctly with melanoma (class MEL).

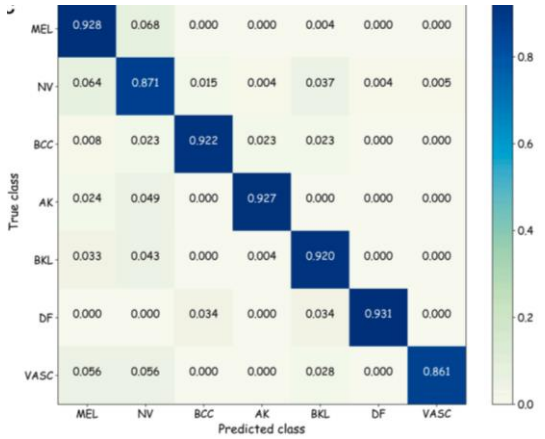


Fig. 5. Confusion matrices on seven skin lesion classes in ISIC-18 [19]

The ROC (Receiver Operating Characteristic Curve) shown in figure 6 is built by sensitivity and specificity values. It is used to compare the effectiveness of different types of classifiers. The area under the curve describes the effectiveness of the classifier, which can take values in the range of 0-1. The closer the curve is to the left right corner of the chart, the larger the field below the graph and the higher the classifier's performance. The ROC curves shown in Figure 6 are an example from the results of the studies presented in [19]. They confirm the high efficiency of the model for the DF class (area = 0.997). For the remaining classes, the area under the ROC curve is smaller and varies in the range of 0.984÷0.996. The lowest area under the curve has an NV class of 0.978.

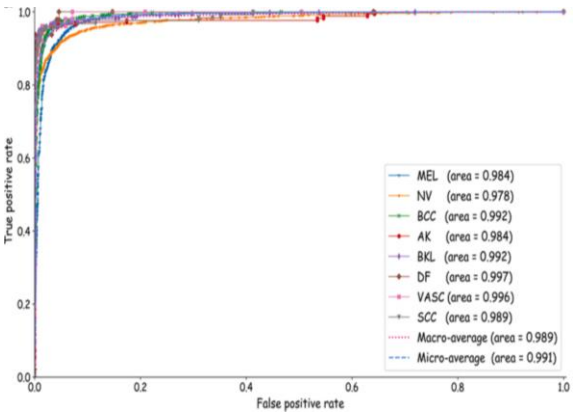


Fig. 6. ROC curves on the test sets foreight skin lesion classes in ISIC-19 MEL – Melanoma, NV – Melanocytic nervi, BCC – Basal cell Carcinoma, AK – Actinic Keratoses, BKL – Benign Keratosis, DF – Dermatofibrom, VASC – Vascular skin lesions, SCC – Squamous cell carcinoma [19]

A very important parameter is sensitivity (True Positive Rate, TPR) is defined as the ratio of true positive (TP) results to the sum of true positive (TP) and false negative (FN). Sensitivity of 100% means that all changes of character for the state of the disease have been recognized. Table 3 provides a list of selected works in which the most frequently mentioned parameters determined during network testing are determined. Among them are: precision, specificity, accuracy, F1 score, AUROC of proposed DCNN models. [6, 19] compiles a comparison of selected available works carried out in recent years. Examples of values obtained in [3, 7, 19, 24, 37, 41] are shown in table 3.

Increasing the number of classes also affects the F1-score value, as shown in figure 7. F1-score achieved a higher score for 2 classes than for 3. The highest score was achieved by the Inception-ResNet-v2 model with an F1-score of 83% for 2 classes. A larger number of classes is associated with more images, which significantly complicate the operation of the network model. For seven classes, the ResNet-50 network achieved the highest score than for 2 classes.

Table 3. Results of comparative methods [19]

Study	Precision	Sensivity	Specificity	Accuracy	F1 score	AUROC
[37]	91.3%	89.9%	92.2%	89.9%	90.0%	0.890
[7]	89.0%	83.0%	-	83.2%	83.0%	-
[41]	-	-	92%	85.3%	-	-
[24]	-	87.3%	82.2%	87.7%	-	0.914
[19]	90.5%	88.8%	95.7%	88.8%	89.1%	0.989
[3]		81.8%	71.4%	81.79%	82.6%	

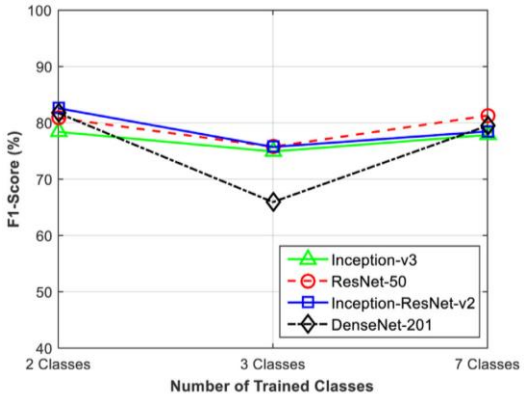


Fig. 7. F1-score values for training classes on different classification [3]

5. Discussion and conclusions

The examples of research listed in the article give a cross-section of the networks used for multi-class classification. They turned out to be the best solutions to the diagnostic tasks set – the classification of skin lesions. The classification concerned images of skin lesions, regardless of the form of the data set and the set of features. Of course, the teaching and test data for each of the works differ. Differences may result from the different number of sets and classes or the set of characteristic features itself. Where there are many available networks, types and methods of classification, it is important to compare the results obtained for a wider spectrum of available methods. The use of more methods in research allows you to be sure that the right choice of method has been made. The obtained results allowed to select the most effective sets of features for the construction of classification models.

Analysis of the results of network training allows you to assess the impact of the abundance of the set and selected dermatoscopic images. The use of a larger data set resulted in high accuracy for these networks. The size of the data set has a significant impact on the accuracy of traditional and deep learning models. The analysis of the results of network testing on smaller data sets presented allows us to conclude that the high results obtained during training were possible thanks to the use of models that were previously trained on a large data set (transfer learning). When testing databases, most often researchers use models VGG16, VGG19, ResNet50, DenseNet201. They also achieve high results during training.

Models built with the use of color images offer the highest classification efficiency, color images have the highest informational load capacity. The data corresponding to images of skin lesions are complex and difficult to classify. The included notes and observations can be helpful in solving other binary and multiclass classification tasks as well. With the continuous development of available models of deep networks and available methods of classification, more and more work will be created on this topic. The resulting research will contribute in the future to increasing the diagnostic effectiveness of skin diseases.

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