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NEURAL NETWORKS FROM KERAS IN SKIN LESION DIAGNOSTIC

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Abstract. *Melanoma is currently one of the most dangerous skin diseases, in addition many others appear in the population. Scientists are developing techniques for early non-invasive skin lesions diagnosis from dermatoscopic images, for this purpose neural networks are increasingly used. Many tools are being developed to allow for faster implementation of the network, including the Keras package. The article presents selected methods of diagnosing skin diseases, including the process of classification, features selection, extracting the skin lesion from the whole image.The described methods have been implemented using deep neural networks available in the Keras package. The article draws attention to the effectiveness, specificity, accuracy of classification based on available data sets, attention was paid to tools that allow for more effective operation of algorithms.*

Keywords: dermatoscopic images, deep learning, melanoma, skin lesions, Keras

SIECI NEURONOWE Z KERAS W DIAGNOSTYCE ZMIAN SKÓRNYCH

Streszczenie. *Melanoma jest obecnie jedną z najbardziej niebezpiecznych chorób skóry, oprócz niej pojawia się w populacji wiele innych. Naukowcy rozwijają techniki wczesnego nieinwazyjnego diagnozowania zmian skórnych z obrazów dermatoskopowych, w tym celu coraz częściej wykorzystywane są sieci neuronowe. Powstaje wiele narzędzi powzalajcych na szybszą implementację sieci należy do niej pakiet Keras. W artykule przedstawiono wybrane metody diagnostyki chorób skóry, należy do nich proces klasyfikacji, selekcji cech, wyodrębnienia zmiany skórnej z całego obrazu. Opisane metody zostały zostały zaimplementowane za pomocą dostępnych w pakiecie Keras głębokich sieci neuronowych. W artykule zwrócono uwagę na skuteczność, specyficzność, dokładność klasyfikacji w oparciu o dostępne zestawy danych, zwrócono uwagę na narzędzi pozwalające na efektywniejsze działanie algorytmów.*

Słowa kluczowe: obrazy dermatoskopowe, uczenie głębokie, melanoma, zmiany skórne, Keras

Introduction

Skin diseases develop more and more often. The most dangerous of them is the rapidly developing malignat melanoma. In the process of diagnosing these diseases, doctors are helped by many other tools. Nowadays, diagnostic tools based on the use of artificial intelligence are being created [10, 12, 16, 36]. The fastest growing field is neural networks. They present in various ways extensive structures, they contain different counts of layers, weights, their operation is characterized by a different time needed to perform the whole process. Deep neural networks consist of many layers, each of which identifies more complex elements of the input image.

Neural networks allow for a number of actions. These include dermatoscopic images segmentation from different regions of the body, for this purpose very good are deep convolutional neural networks – DCNN [11, 19, 28]. The classification of skin lesions images is also important. A binary classification is distinguished, which applies to 2 classes, classification on malignat melanoma versus no-melanoma or begin nevi [6, 15, 22]. Multiclass classification gives the opportunity for greater interest in skin lesions diagnosis processes. The multi-stranded networks development has resulted in the development of its use. It is used for diagnosis based on network models that allow classification into 3, 5 and even 7 different disease [23, 24]. A more complex structure becomes more effective for data with greater diversity. Convolutional networks have allowed scientists to achieve great success in the features selection [1, 21]. In [34] based on the ResNet-50 based supervised deep learning networks gets extracted features from dermatoscopic images.

There are also many works that provide an overview of the available methods based on deep learning and machine learning [14, 26, 35]. The systems also combine multiple modalities to achieve the best possible effect [37]. Used frequently deep learning [8] approach based on CNN and recurrent neural network (RNN) [4]. Many works are based on deep learning [9, 36] and a Deep Residual Network (DRN), deep region based convolutional neural network (RCNN), fully convolutional neural network (FCN) and a specific convolutional neural network (CNN) in [4].

1. Segmentation and classification methods

Many studies have been conducted in melanoma classification from dermatoscopic images using deep learning and neural networks. To that date, there is no accurate data on the clinical use of artificial intelligence. There is a lack of a large data set to train and test algorithms [13]. Currently, the larger database is ISCI, it is a dataset for 7 different skin lesions. The correct diagnosis of skin cancer is not simple, many automated computer diagnostic systems based on deep neural network algorithms are being created.

Many scientists use the Keras library in their work with deep neural networks. It contains more than 20 models of neural networks, e.g. VGG16, VGG19 ResNet50, InceptionV3, MobileNet, InceptionResNetV2. Keras is implemented in Python. It allows you to define high-level blocks and train deep learning models, does not support low-level operations. It relies on a specialized and optimized tensor library (TensorFlow). Many convolutional neural network from Keras has been used for features extraction in many works [2, 3, 7]. They are characterized by different network complexity, number of layers, parameters and iteration time. They have a size from 88 to even 343 MB. Table 1 shows the models listed.

Table 1. Selected Keras networks models https://keras.io/api/applications/

Model	Size (MB)	Top-1 Accuracy	Top-5 Accuracy	Parameters	Depth	Time (ms) per inference step (CPU)	Time (ms) per inference step (GPU)
Xception	88	0.790	0.945	22,910,480	126	109.42	8.06
VGG16	528	0.713	0.901	138,357,544	23	69.50	4.16
VGG19	549	0.713	0.900	143,667,240	26	84.75	4.38
ResNet50	98	0.749	0.921	25,636,712	-	58.20	4.55
ResNet101	171	0.764	0.928	44,707,176	-	89.59	5.19
ResNet152	232	0.766	0.931	60,419,944	-	127.43	6.54
ResNet50V2	98	0.760	0.930	25,613,800	-	45.63	4.42
ResNet101V2	171	0.772	0.938	44,675,560	-	72.73	5.43
ResNet152V2	232	0.780	0.942	60,380,648	-	107.50	6.64
InceptionV3	92	0.779	0.937	23,851,784	159	42.25	6.86
InceptionResNetV2	215	0.803	0.953	55,873,736	572	130.19	10.02
MobileNet	16	0.704	0.895	4,253,864	88	22.60	3.44
MobileNetV2	14	0.713	0.901	3,538,984	88	25.90	3.83
DenseNet121	33	0.750	0.923	8,062,504	121	77.14	5.38
DenseNet169	57	0.762	0.932	14,307,880	169	96.40	6.28
DenseNet201	80	0.773	0.936	20,242,984	201	127.24	6.67
NASNetMobile	23	0.744	0.919	5,326,716	-	27.04	6.70
NASNetLarge	343	0.825	0.960	88,949,818	-	344.51	19.96
EfficientNetB0	29	-	-	5,330,571	-	46.00	4.91

In [30], several models of CNN neural network algorithms were used to determine their effectiveness in the diagnosis of several skin diseases and analysed their efficiency. Was used

Keras Sequential API and transfer learning model includes VGG11, RESNET50, DENSENET121, achieve highest accuracy of 90%. In [30], several models of CNN neural network algorithms were used to determine their effectiveness in several skin diseases diagnosis and analysed their efficiency. The solution is based on VGGNet and the transfer learning paradigm, a sensitivity value of 78.66%, which is much higher than the state of the current technic state in this dataset. Method achieves a sensitivity value of 78.66%.

2. Lesions classification process

The classification can be based on a set of data divided into 3, 6 or even 10 classes depending on how large the database is. Deep neural networks allow you to recognize even several skin diseases at the same time. More extensive classification systems allow you to assess more skin diseases causing the formation of various birthmarks. Figure 1 shows 8 pictures of selected skin diseases. The right number of these images allows you to evaluate as many as 8 different classes.

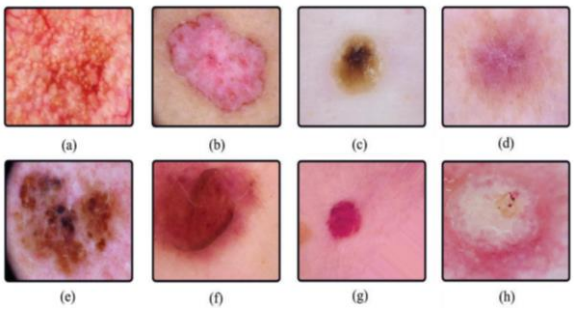


Fig. 1. Sample images of each class: (a) actinic keratoses, (b) basal cell carcinoma, (c) benign keratosis, (d) dermatofibroma, (e) melanoma, (f) melanocytic nervi, (g) vascular skin lesions, (h) squamous cell carcinoma [33]

Many works [6, 14, 15, 22] have been devoted to binary classification, which are based on extensive databases of dermatoscopic images confirmed by biopsy. Researchers use over 500 or even 1500 images. Figure 2 shows the steps of binary classification by the selected CNN network. The first step is to find databases that will contain as many cases as possible and good quality images without artifacts that prevent network diagnostics. The images are preprocessed, then the samples are cropped from the processed images. They are the ones who are classified. In earlier years, the most frequently chosen classification by scientists was binary. It concerns divisions into 2 classes, most often into malignat melanoma versus benign nevi (benign nonpigmented skin lesions, versus melanocytic nevi or atypical nevi) [14, 29].

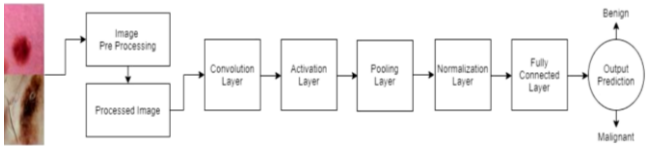


Fig. 2. CNN architecture from [29]used for binary classification

Batch normalization was used in the network architecture from [29]. It is reasonable to improve the performance, stability of the deep neural network, normalizes the input layer, removes parameters that reduce the performance of the model. Depending on the number of layers, the entered parameters, the classification process gives a different effect. In assessing the created model effectiveness, graphs of accuracy and loss values in relation to the number of epochs made by the network (figure 3) help. On the basis of the distribution of values for training and validation data, the algorithm or the type of data used is modified accordingly. It is important that the network is well trained, not retened, and that the data is well matched to the model.

In [33], neural networks from the Keras library were used to classify skin lesions: DenseNet-201, Inception-ResNet-V2 and Inception-V3. Figure 4 shows promising results and compares them. Inception-ResNet-V2 and Inception-V3 show similar results they have in terms of algorithm accuracy and losses. DenseNet-201 achieved the highest values of data validation efficiency, as well as the lowest loss values. Comparing several algorithms with each other allows you to find the best one, ensuring the highest efficiency.

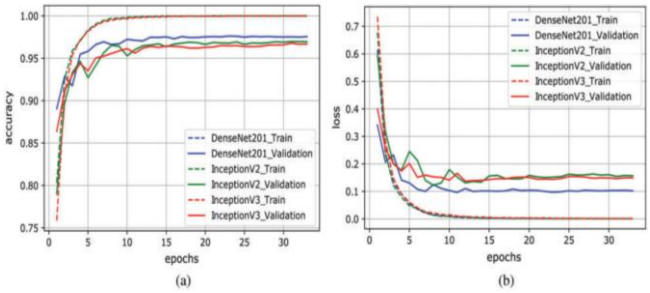


Fig. 3. Evolution of training and validation for (a) accuracy and (b) loss of the proposed model [33]

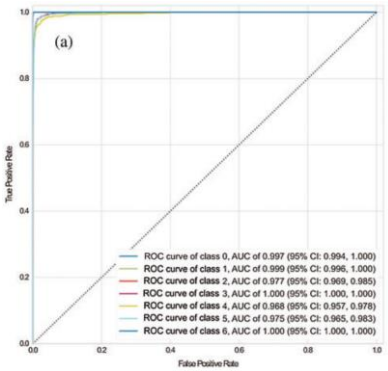


Fig. 4. ROC Curves with a confidence interval of 95% for 6 classes (0 'akiec' – actinic keratoses, 1 'bcc' – basal cell carcinoma, 2 'bkl' – benign keratosis, 3 'df' – dermatofibroma, 4 'mel' – Melanoma, 5 'nv' – melanocytic nervi, and 6 'vasc' – vascular skin lesions) [33]

The development of the ROC diagnostic curve gives a broader picture of the results obtained. The closer the curve to 1 in the TruePositive Rate, the higher the diagnostic capabilities of the algorithm. In [33] was obtained an average accuracy of 98% for all 6 classes with DenseNet-201. Classes 4 (melanoma disease) and 6 (Vascular skin lesions) were diagnosed with the highest success rate, reaching 1, and 0.999 for class 1 (basal cell carcinoma disease).

3. Features extraction

Many works are being created that allow for skin lesions diagnosis from dermatoscopic images. Researchers in the work on feature extration based on CNN architecture focus on geometry-based [20], color-based data augmentation [25] and ensemble of network architectures [17].

In [3] using binary classification, feature extraction was made. Two classes were considered, the first with images of melanoma and second colled „no melanoma" with unknow nad begin lesions. The results are presented in Figure 5. The authors were the first to combine RGB composition with the addition of texture information for relevant points. For this purpose, they generated key points with first-order statistical information, second-order statistical parameters. Then, the RGB components were analyzed to extract the features needed in the training set. A network with appropriately selected images was trained and classifications were made. The algorithm was based on finding points regardless of the location of the image.

In [21] a new function has been introduced – the difference between the maximum and minimum diameter of the Feret. It is assumed that it is the best suited ellipse to the shape of the skin lesion, using it melanoma was classified with an accuracy of up to 86.5%. The result of this step is a binary image of an segmented white skin lesion on a black skin background. To distinguish between malignant and benign melanoma, a neural network (BNN) back-propagation model was created. The results of the activities are presented in figure 6 Numerical values for various features AS1, AS2, B, C, D1, D2 have been quantified.

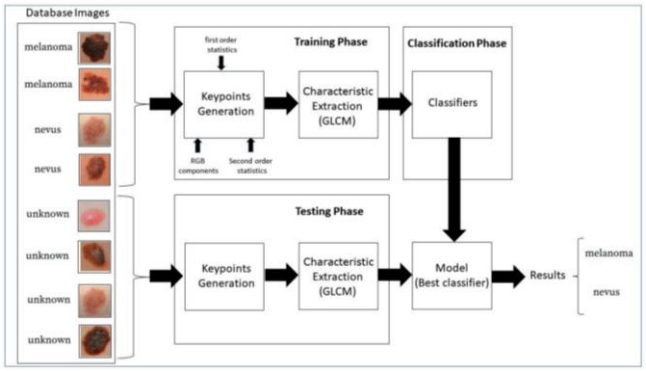


Fig. 5. Classification algorithm proposed in [3]

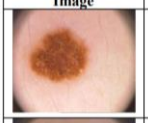
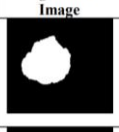
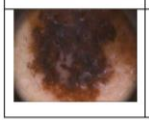
Original Image	Segmented Image	Features	Output
		*AS1*: 0.13 *AS2*: 0.13 *B*: 0.86 *C*: 2 *D1*: 4 *D2*: 0.96	Benign
		*AS1*: 0.16 *AS2*: 0.18 *B*: 0.86 *C*: 1 *D1*: 4.3 *D2*: 0.46	Benign
		*AS1*: 0.24 *AS2*: 0.18 *B*: 0.5 *C*: 4 *D1*: 8.6 *D2*: 1.5	Malignant

Fig. 6. Results from [21]

Scientists also try to modify the structure of the network in various ways. For feature extration in [18] was used Lesion Feature Network (LFN). The architecture of this network is shown in figure 7 Blue rectangles represent 12 convolution layers, the numbers on them indicate the size and number of kernels. The layers consist of 3×3 and 1×1 spots. 1×1 weave helps to integrate the functions created in 3×3. MP, AP, FC wool in the structure still other functions. Calculating softmax losses allows you to pay more attention to classes with fewer samples.

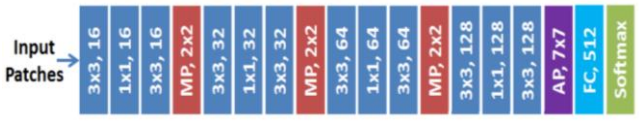


Fig. 7. Flowchart of Lesion Feature Network (LFN) [18]

4. Supporting functions and tools

Currently, a lot of work is aimed at tuning already pre-trained CNN networks with their known parameters. It is then used for well-prepared data, which is properly enlarged, important features are detailed. One should not forget about the sufficiently numerous classes, in an appropriate way divided into them images [5, 34]. Many face the problem of excessive do-fitting when working. One of the basic tools is a good preparation of input images, geometric transformations are made, images are scaled, colors are transformed. However, there are still a number of factors that affect the final result.

Beyond the structure of the neural network itself. An important element of the network is the optimizer, which determines the course of training. The loss function compares the results of network predictions with the target labels and calculates the loss value based on them. The Optimizer uses them when modifying network weights.

The process of teaching large networks can be time-consuming and require large computing resources. For this reason, it is worth choosing the right optimizer. The most frequently chosen are: momentum optimization, Nesterov algorithm (accelerated drop along the gradient), AdaGrad, RMSProp, Adam algorithm (adaptive moment estimation.

In [2], texture analysis was performed using the CNN model. Classification was made using appropriate labels in 16 classes from the Kylberg Texture dataset. In [2], texture analysis was performed using the CNN model. Classification was made using appropriate labels in 16 classes from the Kylberg Texture dataset. One of the most well-known optimizers is Adam [7], who learns very quickly, has no problems with fading learning indicators, leading to fluctuations in the function of loss.

In [32] the Max Pooling Layer was placed in the network structure. It causes a reduction along the weight and length, it reduces the matrix significantly, this can be seen in figure 8, which results in a smaller numerical representation of the parameters. With the help of the MAX function, the network is spatially reduced. In [16] a Max-Pool of 2×2 size was used, from 4 adjacent fields 1 – figure 8 was obtained.

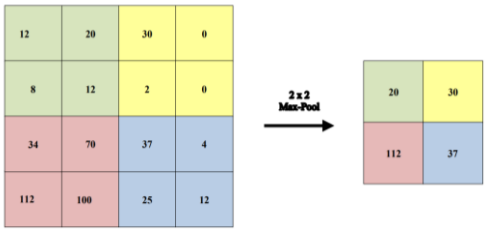


Fig. 8. Examples of how max pooling operates [14]

In the classification processes, other methods are also used to assess the effectiveness of neural networks and increase its effectiveness. Various comparisons of selected methods of melanoma classification are also made. Stolz's conventional method [27] was compared with the result of algorithms from [32]. The research was carried out on 700 samples. The STOLZ method achieved an accuracy of 76.6%, while the proposed one in [32] achieved 96.67%. Due to the emerging artifacts in the images and not very clear boundaries of changes, the STOLZ method has a lower efficiency in the extraction of skin lesion boundaries. Therefore, it incorrectly classifies the areas around the border.

5. Discussion and conclusions

Melanoma is now increasingly diagnosed skin disease. It is important to detect it quickly and fight the disease at an early stage. The development of non-invasive early diagnosis techniques is an issue of interest to many research teams. Neural networks are now becoming the fastest growing field of medical informatics. The use of methods based on various tools allows to increase the effectiveness of diagnosis of melanoma and other skin diseases using deep neural networks.

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