http://doi.org/10.35784/iapgos.3042

received: 31.07.2022 | revised: 24.09.2022 | accepted: 25.09.2022 | available online: 30.09.2022

DEEP NEURAL NETWORKS FOR SKIN LESIONS DIAGNOSTICS

Magdalena Michalska-Ciekańska
Lublin University of Technology, Department of Electronics and Information Technology, Lublin, Poland

Abstract. *Non-invasive diagnosis of skin cancer is extremely necessary. In recent years, deep neural networks and transfer learning have been very popular in the diagnosis of skin diseases. The article contains selected basics of deep neural networks, their interesting applications created in recent years, allowing the classification of skin lesions from available dermatoscopic images.*

Keywords: deep neural networks, transfer learning, dermatoscopic images, skin lesions diagnostics

GŁĘBOKIE SIECI NEURONOWE DLA DIAGNOSTYKI ZMIAN SKÓRNYCH

Streszczenie. *Nieinwazyjna diagnostyka nowotworów skóry jest niezwykle potrzebna. W ostatnich latach bardzo dużym zainteresowaniem w diagnostyce chorób skóry cieszą się głębokie sieci neuronowe i transfer learning. Artykuł zawiera wybrane podstawy głębokich sieci neuronowych, ich ciekawe zastosowania stworzone w ostatnich latach, pozwalające na klasyfikację zmian skórnych z dostępnych obrazów dermatoskopowych.*

Słowa kluczowe: głębokie sieci neuronowe, transfer learning, obrazy dermatoskopowe, diagnostyka zmian skórnych

Introduction

In recent years, skin cancers, and in particular melanoma, have been quite often diagnosed in the world. Malignant melanoma develops in the human body very quickly, according to statistics in 2016 in Poland over 3,600 people fell ill with it, and over 1,300 people died from it [39]. Still, too few patients report skin nevi to dermatologists, and early diagnosis in the case of cancer is crucial. Dermatoscopy comes to the aid of doctors. It allows for non-invasive high-resolution images of the skin. On its basis, doctors make a preliminary diagnosis.

With the help of doctors, diagnostic tools based on artificial intelligence were launched [5, 22]. Deep learning and other machine learning techniques have helped to increase the efficiency of medical image analysis. This is an area of machine learning in which subsequent layers of the network learn with each step better representations based on the information provided. The use of deep convolutional neural networks (DCNN) in recent years has been leading the way in the giagnostics of skin nevi. Many works have been created to effectively diagnose skin cancers [8, 21]. The use of selected segmentation and classification methods allows to achieve even better diagnostic success [12, 17, 28, 37].

Dermatoscopic image databases contain many images of a given case of the disease, which has been confirmed by histopathological examination. Properly prepared, they are input data for the process of training neural networks. The most commonly used databases with diagnosed dermatoscopic images by researchers include: ISIC [18], MED.-NODE [27], PH2 [30], PAD-UFES-20 [29], DERMOFIT [6]. Images from a given class are grouped and subjected to a process of initial preparation, regions of interest (ROI) are distinguished. The next stage is most often the segmentation of the cutaneous birthmark. The beginning of the classification of cutaneous nevi included binary classification [3, 14]. However, further development of technology has made it possible to create more classes. Currently, it is possible to make a classification for 5, 6, 7 and even 10 different skin diseases.

1. Deep neural networks basics

The use of models based on deep learning was possible thanks to the implementation of appropriate algorithms. A multi-layered network model is created and input data is provided to the model in the form of medical images. Each of the many layers of the model processes more complex elements of the input image. Many operations were performed on the images delivered to the network, which ultimately lead to the output. Diagnosis belongs to these data. Deep neural network architectures include: multilayer perceptrons, limited Boltzmann machines, deep belief networks, convolutional neural networks (CNNs), recursive neural networks. Very good effects are observed due to the emergence of new models of convolutional neural networks. Increasing the computing capabilities of computers has slowly moved to the development of new techniques for effective deep network learning. It is possible to diagnose skin cancers and benign lesions from dermatoscopic images more and more effectively.

Convolutional neural networks are the most popular tool used to classify medical images. Convolutional layers, on the other hand, learn local patterns selected from the image. Figure 1 shows typical weave network architecture. The basis of the network is the convolution base. It consists of an input layer and several convolutional layers connected to each other by pooling layers. Neurons are connected to neurons of the higher layer (pooling). Neurons in the convolution layers of the first layer are combined with pixels in the reception fields of the input image. In contrast, neurons from the second layer connect to a small area of the first layer. In the reception fields, e.g. with dimensions of 3×3 or 5×5, there are local patterns that the network finds. In each subsequent hidden layer, the network focuses on more details of a given feature. With more layers, you can analyze features with more detail. The last layer calculates forecasts, often it is a softmax layer. It is designed to estimate the probability of an image belonging to a given specific class.

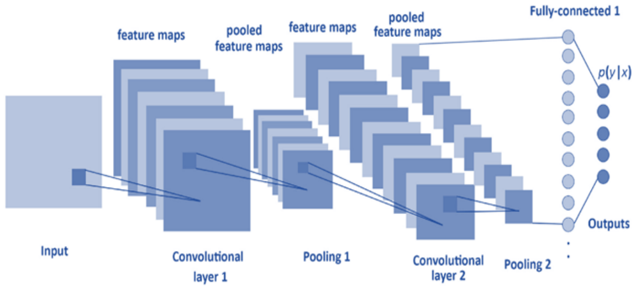


Fig. 1. Typical convolutional network architecture [34]

Linking layers are designed to sub-sample feature maps, reduce the load on algorithm calculations and the number of parameters. They do not need scales, they include the processing of input data by the aggregation function. Extraction windows process feature maps. After the convolution base, there is a classifier. The data contains its representations and the trained model determines for a given image belonging to a specific class, which is determined with a certain probability.

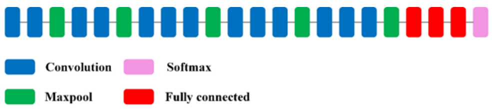
Transfer learning is very helpful in medical diagnostics. This is a type of machine learning that is based on learning new tasks based on previously acquired knowledge. It allows you to increase the efficiency of model learning even for a smaller amount of data. This is important in the case of dermatoscopic images, because not all available databases contain many images to fully reflect the specificity of a given skin disease in the image.

2. Used model examples

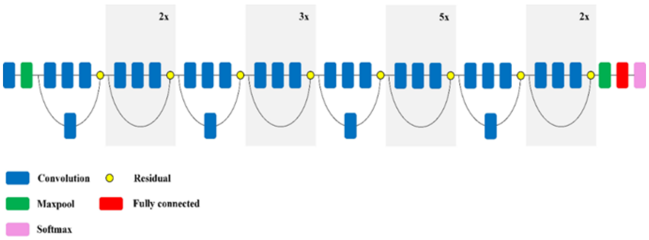
Initially, DNN was used for deep learning using the AlexNet architecture, GoogleNet. There are many network models available today. The basic ones selected for work on medical images include VGG, ResNet, MobileNet [15], DenseNet [16, 37], MobileNetV2 [33], InceptionV3. Some of the networks are created by combining the architecture of 2 or 3 other networks: NASNet, Xception, InceptionV3, InceptionRes-NetV2 and many others. The Keras library [21] is one of the most commonly used in the creation of networks for the classification of skin lesions, it uses transfer learning.

Each of the networks has characteristic elements that build it, including convolution, maxpool, soft max and fully connected layers. However, they differ in the number of layers and connections between them. One of the most frequently tested networks is VGG. This network is characterized by the smallest topological depth with a small 3×3 weave filter. Among the VGG networks, the most successful were two of them VGG16 (figure 2a) and VGG19. VGG16 is made up of 13 convolutional layers and three fully connected layers. Both networks use small 3×3 strand filters. This increases the topological depth of the network and contributes to a more effective learning process.

The ResNet network model [13] is characterized by a very deep structure, has as many as 152 layers. The problems related to the depth of the network include: difficulties in training, high training error, disappearing gradient. In this network, 3×3 filters are most often used. 1×1 convolution layers deepen the lattice and increase nonlinearity by applying the ReLU function after each 1×1 convolution layer. In this network, fully connected layers are replaced with a pooling averaging layer, which reduces the number of parameters. This structure provides the network with learning deeper representations of functions with fewer parameters. The ResNet diagram is shown in figure 2b.



a)



b)

Fig. 2. Diagram of the VGG16 (a) and ResNet (b) network models [24]

3. Application examples

Deep neural networks are used to diagnose many skin diseases, mainly diagnosed cancers from dermatoscopic images are: squamous cell carcinoma, malignat melanoma, basal cell carcinoma. Among the most commonly diagnosed benign skin birthmarks should be mentioned: nevus, pigmented benign keratosis and seborrheic keratosis. Diagnostic systems based on deep neural networks allow to make binary classification, but also in high efficiency recognize simultaneously 3 [25], 5 [26], 7 [4, 36], 8 [37] and even 10 [10] different classes.

The use of machine learning tools, artificial intelligence and neural networks competes very effectively with human knowledge [10]. Figure 3 shows the entire scheme of action when selecting the segmentation of skin lesions and their classification. It takes into account the selection of the most popular databases of dermatoscopic images, the selection of the segmentation method and the selection of the network model needed for binary or multi-class classification. It assumes obtaining results based on a binary classification and two multi-class classifications (3 classes and 7 classes). Individual classes are marked with letters: include benign (B), seborrheic keratosis (SK), basal cell carcinoma (BCC), actinic keratosis (AK), dermatofibroma (DF), vascular lesion (VL) and melanoma (M).

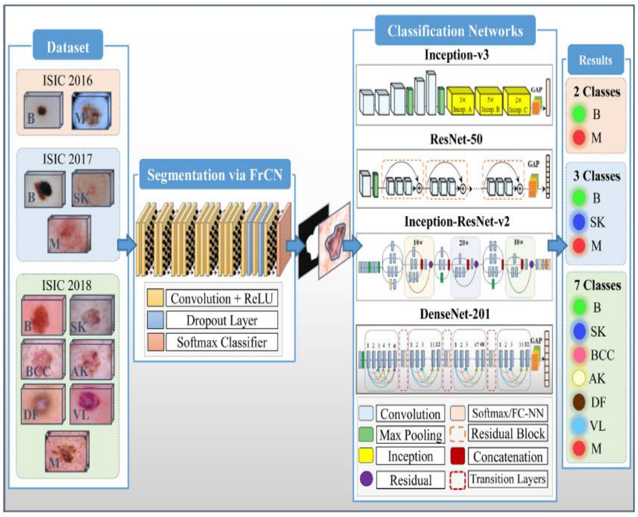


Fig. 3. An exemplary scheme of action during segmentation and classification of skin lesions [2]

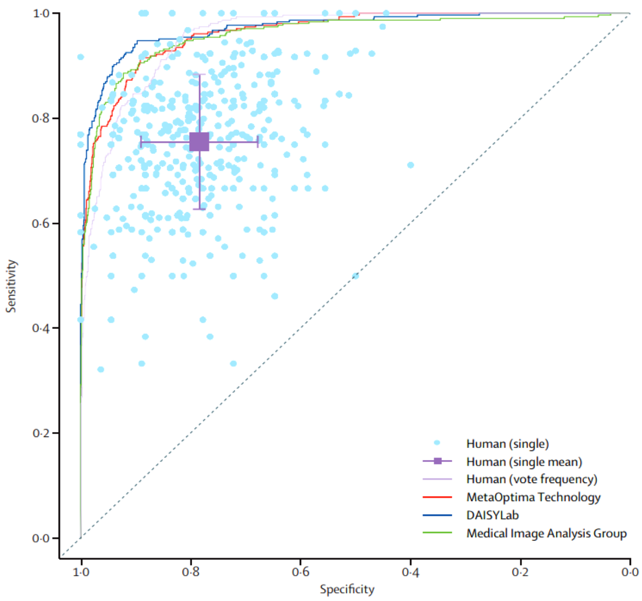


Fig. 4. ROC curves for test groups [36]

Works comparing the diagnostic capabilities of algorithms and experienced doctors are being created. In [36], the researchers undertook extensive research that aimed to compare the diagnoses of medics with randomly selected images. The results of the doctors' diagnoses were compared with more than 130 machine learning algorithms from the International Skin Imaging Collaboration 2018. Among the medics were board-certified dermatologists, dermatology residents and general practitioners. Figure 4 shows ROC curves for diagnostic efficacy to distinguish between malignant and benign skin lesions. The graph compares diagnostic capabilities single human (blue dots), vote human frequency (purple line), MetaOpima Technology (red line), DAISYLab (dark blue line) and Medical Images Analysis Group (green line). Higher diagnostic efficiency is achieved by algorithms using machine learning than human diagnostic capabilities.

Achieving high diagnostic effectiveness of algorithms based on DNN is possible due to the use of properly selected databases, selection of images for training, validation and test sets. Choosing network models and properly tuning its parameters is also not a simple task. It is also important to choose the number of epochs when training the network.

Each of the teams tries to draw knowledge and experience from the work already developed so that there is a continuous development of algorithms. Often, the achievements of several researchers are modified and combined into one work [35]. To obtain a high AUROC value, the classification layers of several models are combined into one, which ensured the competitiveness of such modified models [11, 23]. High-resolution dermatoscopic images are also used for classification to more effectively use patches-based models of skin lesion [9]. Table 1 shows the results for segmentation and classification using deep neural networks. Their accuracy ranges from over 80% to almost 98%. They also use transfer learning.

Table 1. Results for the segmentation and classification CNN's models in recent years

Authors	Used metod	Accuracy
[38]	Transfer Learning using VGG16	80.3%
[20]	Transfer Learning using ResNet50	83.5%
[32]	Transfer Learning using DenseNet201	95.9%
[1]	Stacking ensemble of fine-tuned models	97.9%
[7]	ResNet-50	95.8%
[7]	Xception	92.9%
[31]	Transfer Learning using ResNet50 GANs	95,2%
[2]	ResNet-50	81.6%

There are also works that modify known network models, models are also created that connect them with each other. In [1] the Stacking ensemble of fine-tuned models shown in figure 5 was created, it combines 4 network models: Xception, DenseNet201, DenceNet121 and Inception-ResNet-V2 and gives satisfactory results, its accuracy is 97.9%. The cumulative model was created to increase the efficiency of the best 4 network models. The use of team learning reduces variance. The presented concept assumes deep learning of stacked 4 models of pre-trained models. Stacking is a modification of the averaging unit. He is responsible for teaching the new model by combining already existing submodels.

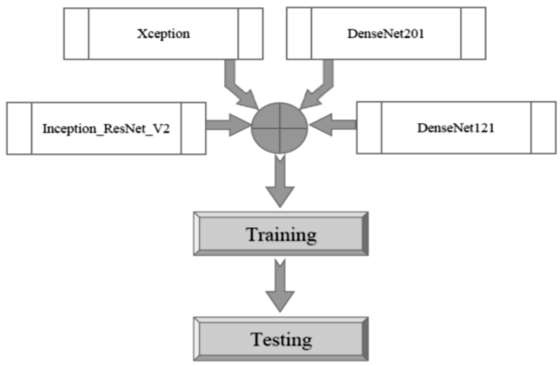


Fig. 5. Diagram of stacked ensemble model [1]

Also intriguing are deep learning techniques contraindicated on full convolutional networks (FCNs). They become effective in segment the image by using a huge amount of data during multi-level learning. Figure 6 shows the architecture of this network model.

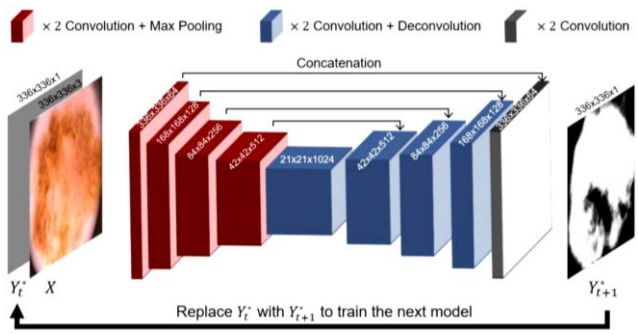


Fig. 6. Full architecture of the model from [19]

4. Discussion and conclusions

The methods proposed in the work are helpful in non-invasive diagnosis of skin lesions. They can effectively identify skin diseases based on dermatoscopic images. It is assumed that the ideal solution would be the testing of automated diagnostic systems based on deep neural networks by experienced dermatologists. This would make these 2 groups angry and help many people regain their health. In the future, automatic classifiers will work under human supervision. Further development of all methods based on deep neural networks and transfer learning will definitely increase the effectiveness of skin lesions diagnostics.

References

[1] Abunadi I., Senan E. M.: Deep learning and machine learning techniques of diagnosis dermoscopy images for early detection of skin diseases. Electronics 10, 3158, 2021 [http://doi.org/10.3390/ electronics10243158].
[2] Al-Masni M. A., Kim D. H., Kim T. S:. Multiple skin lesions diagnostics via integrated deep convolutional networks for segmentation and classification. Comput Methods Programs Biomed. 190, 105351, 2020 [http://doi.org/10.1016/j.cmpb.2020.105351].
[3] Brinker T. J. et al: Deep learning outperformed 136 of 157 dermatologists in a head-to-head der moscopic melanoma image classification task. Eur J Cancer 113, 47–54, 2019.
[4] Chaturvedi S. S., Gupta K., Prasad P. S.: Skin lesion analyser: An efficient seven-way multi-class skin cancer classification using MobileNet. Advances in Intelligent Systems and Computing 1141, Springer, Singapore, 2020 [http://doi.org/10.1007/978-981-15-3383-9_15].
[5] Codella N. C. F. et al.: Deep learning ensembles for melanoma recognition in dermoscopy images. IBM Journal of Research and Development 61(4/5), 173, 2017.
[6] DERMOFIT IMAGE LIBRARY [https://licensing.edinburghinnovations.ed.ac.uk/i/software/dermofit-imagelibrary.html?item=dermofit-image-library] (accessed 04.01.2021).
[7] Gavrilov D., Lazarenko L., Zakirov E.: AI recognition in skin pathologies detection. Proceedings of the 2019 International Conference on Artificial Intelligence: Applications and Innovations (IC-AIAI), 554–542, Belgrade 2019.
[8] Ge Y. et al.: Melanoma segmentation and classification in clinical images using deep learning. 10th International Conference on Machine Learning and Computing ICMLC, 2018, 252–256.
[9] Gessert N. et al.: Skin lesion classification using CNNs with patch-based attention and diagnosis-guided loss weighting. IEEE Trans. Biomed. Eng. 67, 495–503, 2020.
[10] Haenssle H. A. et al: Man against machine reloaded: performance of a market-approved convolutional neural network in classifying a broad spectrum of skin lesions in comparison with 96 dermato-logists working under less artificial conditions. Ann Oncol 31, 137–143, 2020.
[11] Harangi B.: Skin lesion classification with ensembles of deep convolutional neural networks. J. Biomed. Inform. 86, 25–32, 2018 [http://doi.org/10.1016/j.jbi.2018.08.006].
[12] Hasan M. M., Elahi M., Alam M. A.: DermoExpert: Skin lesion classification using a hybrid convolutional neural network through segmentation, transfer learning and augmentation. medRxiv 2021.02.02.21251038 [http://doi.org/10.1101/2021.02.02.21251038].
[13] He K. et al.: Deep residual learning for image recognition. IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2016, 770–778.
[14] Hekler A. et al.: Deep learning outperformed 11 pathologists in the classification of histopathological melanoma images, Eur J Cancer 118, 91–96, 2019.
[15] Howard A. G. et al.: MobileNets: Efficient convolutional neural networks for mobile vision applications. Computer Science, Computer Vision and Pattern Recognition, arXiv:1704.04861v1 [http://doi.org/10.48550/arXiv.1704.04861].
[16] Huang G. et al.: Densely Connected Convolutional Networks. Computer Vision and Pattern Recognition arXiv:1608.06993v5 [http://doi.org/10.48550/arXiv.1608.06993].
[17] Iqbal I. et al.: Automated multi-class classification of skin lesions through deep convolutional neural network with dermoscopic images. Computerized Medical Imaging and Graphics 88, 101843, 2021 [http://doi.org/10.1016/j.compmedimag.2020.101843].
[18] ISIC Archive [https://www.isic-archive.com/#!/topWithHeader/onlyHeaderTop/gallery] (accessed 23.03.2022).
[19] Kareem O., Mohsin Abdulazeez A., Zeebaree D.: Skin Lesions Classification Using Deep Learning Techniques: Review. Asian Journal of Research in Computer Science 9(1), 1–22, 2021 [http://doi.org/10.9734/AJRCOS/2021/v9i130210].
[20] Lee S. et al.: Augmented decision-making for acrallentiginous melanoma detection using deep convolutional neural networks. J. Eur. Acad. Dermatol. Venereol. 34, 1842–1850, 2020.
[21] Lopez A. R. et al.: Skin lesion classification from dermatoscopic images using deep learning techniques. 13th International Conference on Biomedical Engineering (BioMed) IASTED, 2017, 49–54 [http://doi.org/10.2316/P.2017.852-053].

[22] Maglogiannis I., Doukas C. N.: Overview of advanced computer vision systems for skin lesions characterization, IEEE transactions on information technology in biomedicine 13(5), 721–733, 2009.

[23] Mahbod A. et al.: Fusing finetuned deep features for skin lesion classification, Comput. Med. Imaging Graph. 71, 19–29, 2019 [http://doi.org/10.1016/j.compmedimag.2018.10.007].

[24] Mahdianpari M. et al.: Very deep convolutional neural networks for complex land cover mapping using multispectral remote sensing imagery. Remote Sens. 10(7), 2018.

[25] Marchetti M. A. et al.: Computer algorithms show potential for improving dermatologists' accuracy to diagnose cutaneous melanoma: results of the international skin imaging collaboration 2017. J Am Acad Dermatol 82, 622–627, 2020.

[26] Maron R. C. et al.: Systematic outperformance of 112 dermato-logists in multiclass skin cancer image classification by convo-lutional neural networks, Eur J Cancer 119, 57–65, 2019.

[27] MED-NODE Dataset [http://www.cs.rug.nl/~imaging/databases/melanoma_naevi/] (accessed 23.03.2022).

[28] Nida N. et al.: Melanoma lesion detection and segmentation using deep region based convolutional neural network and fuzzy C-means clustering, International Journal of Medical Informatics 124, 37–48, 2019.

[29] PAD-UFES-20 Dataset [https://data.mendeley.com/datasets/zr7vgbcyr2/1] (accessed: 23.03.2022).

[30] PH2 Dataset [https://www.fc.up.pt/addi/ph2%20database.html] (accessed 23.03.2022).

[31] Qin Z. et al.: A GAN-based image synthesis method for skin lesion classification. Computer Methods and Programs in Biomedicine, 105568, 2020.

[32] Raza R. et al.: Melanoma Classification from dermoscopy images using ensemble of convolutional neural networks. Mathematics 10, 26, 2022 [http://doi.org/10.3390/math10010026].

[33] Sandler M. et al.: MobileNetV2: Inverted Residuals and Linear Bottlenecks. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2018, 4510–4520.

[34] Simonyan K., Zisserman A.: Very deep convolutional networks for large-scale image recognition. International Conference on Learning Representations ICLR, 2015.

[35] Szegedy C. et al.: Inception-v4, Inception-ResNet and the impact of residual connections on learning. AAAI, 4278–4284, 2017 [http://doi.org/arXiv:1602.07261].

[36] Tschandl P. et al.: Comparison of the accuracy of human readers versus machine-learning algorithms for pigmented skin lesion classification: an open, webbased, international, diagnostic study. Lancet Oncol 2019b(20), 938–947, 2019.

[37] Villa-Pulgarin J. et al.: Optimized convolutional neural network models for skin lesion classification, Computers, Materials & Continua Tech Science Press, CMC 70(2), 2022

[38] Yu C. et al.: Acral melanoma detection using a convolutional neural network for dermoscopy images. PLoS ONE 2018, 13, e0193321, 2018.

[39] Zakład Epidemiologii i Prewencji Nowotworów Centrum Onkologii – Instytut w Warszawie. Krajowy Rejestr Nowotworów (KRN) [http://onkologia.org.pl/] (accessed 02.08.2019).

M.Sc. Magdalena Michalska-Ciekańska
e-mail: magdalena.michalska@pollub.edu.pl

Ph.D. student at Department of Electronics and Information Technology, Lublin University of Technology. Recent graduate Warsaw University of Technology The Faculty Electronics and Information Technology. Her research interests include medical image processing, optoelectronics, spectrophotometry.

http://orcid.org/0000-0002-0874-3285