Automatic diagnosis system for classification, segmentation, detection and tracking of Skin lesion based on Deep convolutional neural networks

S.Benyahia
University Mustapha Stambouli department of computer science
Mascara, Algeria
benyahia.samia@univ-mascara.dz

B.Meftah
University Mustapha Stambouli department of computer science
Mascara, Algeria
boudjelal.meftah@univ-mascara.dz

Abstract—This paper presents a review of the state-of-the-art convolutional neural network based deep learning techniques, used for skin lesion analysis specially the problem of Melanoma including lesion segmentation; lesion classification; and lesion detection and tracking, In recent years CNN, based methods would greatly benefit the advancement of skin lesion diagnosis and gained more popularity in this domain. This paper gives an important contribution to this research area and summaries the research being done in different tasks used in the literature for Deep learning and developing an automatic diagnostic system for skin cancer.

Keywords— deep learning, convolutional neural networks, classification, segmentation, detection, tracking, review.

I. Introduction

Skin is the largest organ of a human body, functions of skin in human body have a greater importance they protect against infection and injury and helps to regulate body temperature; a small change in its functioning might affect other parts of the body. Skin is exposed to outer environment thus the disease and infection occurs more to skin. Skin is composed of the epidermis, the dermis and the subcutaneous tissue. The epidermis consists two part of cells, the melanocytes and the keratinocytes, which are producing melanin , that protects against the harmful, this latter may create darker accumulations, known as nevi and under some occasions the skin cells multiply rapidly and form tumors as: Actinic keratosis, Atypical moles, Melanoma, Merkel cell carcinoma, basal cell carcinoma, squamous cell carcinoma [1], some of these causes are : ultraviolet radiation from sunshine, many moles, previous illness, age, as risk increases with age ,family or personal history of melanoma, having an organ transplant, white skin that burns easily [5]. Melanoma present 1% of the diagnosed cases of skin cancer and cause 75% of related deaths [4].

Clinical research has shown that Skin lesion is the most common human malignancy a severe globally. Despite its prevalence, it is a disease that is not well understood by many. Computerized analysis of skin lesions is usually performed on two categories of input images as dermoscopic (microscopic images) and non dermoscopic (macroscopic or clinical images), It is shown that dermoscopic examination by trained and experienced dermatologists yields better sensitivity and specificity [2] in skin lesion diagnosis, and increase the survival rate [3]; dermoscopic images are produced by dermatoscope, a special instrument that facilitates the procedure of inspection by magnifying the lesion and providing uniform illumination of skin region for increased clarity of the spots, which enhances the visual effect of skin lesion by removing surface reflection and to help dermatologists in examining pigmented skin lesions due to the low contrast between skin lesions and normal skin regions, the irregular and fuzzy lesion borders, infraclass variation of lesions in terms of color, texture, shape, size and location the existence of various artifacts either natural (hairs, veins) or artificial (air bubbles, ruler marks, color calibration) in the dermoscopy images , and various imaging acquisition conditions. Nevertheless, automatic recognition of melanoma from dermoscopy images is still a difficult task, as it has several challenges, for this the dermatologists have developed various metrics for evaluation of skin lesions for malignancy, such as “3-point checklist”, “Menzies method” [6] the seven-point checklist [7] and ABCDE criterion (A - asymmetry of the lesion, B -border irregularity, C - color variation, D - diameter, and E – evolution over time) [8].

A hard effort is being made as part of the “International Skin Imaging Collaboration ” (ISIC) [9] to organize an archive annotated by experts as a public resource of images in order push the development of dermoscopic image analysis tools for automated diagnostic. The ISIC project organized the ISBI challenges that provides annotated images as training data to engage in (lesion segmentation; detection and localization of features, and disease classification), and a separate test dataset for the evaluation of the results.

In 2018, a new challenge was organized with three tasks: First is to predict boundary and segmentation masks from dermoscopic images with 2600 images for training, 100 for validation, 1000 for test. Second is lesion attribute detection with 2600 images for training, 100 for validation, 1000 for test, and the Third is disease classification between “Melanoma”, “Melanocytic nevus”, “Basal cell carcinoma”, “Actinic keratosis / Bowen’s disease (intraepithelial carcinoma)”, “Benign keratosis (solar lentigo / seborrheic keratosis / lichen planus-like keratosis)”, “Dermatofibroma”, and “Vascular lesion”, with 10,000 images for training, 200 for validation, 1500 for test [10]. As it is well known there is not enough experienced dermatologists all over the world.

In order to solve this problem , there has been effort to create automatic image analysis software using dermoscopy images based on deep learning approaches

The next section reviews the state-of-the-art using a Deep Learning approach in particular convolutional networks Neural Networks (CNNs) for the problem of skin lesion analysis, more specifically for segmentation, classification and detection and tracking of skin lesions.

II. Deep Learning

Deep learning (DL) is a branch of machine learning based on artificial neural networks, it can be applied to supervised and unsupervised learning tasks. the Deep learning mimics the way information is processed in human brain using multiple layers of transformation with numerous techniques and requiring great computational power and large amounts of annotated data, it is also often involving dozens of hyperparameters. Deep learning has been demonstrated to be able to achieve both human and super-human levels of performance and emerged as one of the top research successfully applied to many real-world applications. Particularly where large amount of data needs to be analyzed.

Deep convolutional neural networks (DCNN) are able to learn hierarchies of invariant features and usually require a large amount of training data in order to avoid overfitting.

DCNN stacking several layers where the output of preceding layer is used as an input for the next layer . The most common layers employed in DCNN are convolution, ReLU (Rectified Linear Units), tanh (Hyperbolic Tangent Function), max pooling, average pooling, fully connected, dropout and softmax. Several DCNN models have been proposed such as AlexNet [11], VGG [12], GoogleNet [13], Residual Net [14], DenseNet [15], and CapsuleNet [16].

CNN have dramatically provided state-of-the-art performance for skin lesion diagnosis due to the use of activation functions and optimization techniques that resolve training problems and the dropout to regularize the networks.

Transfer learning or fine-tuning has also been explored in deep learning using a pre-trained neural network, and provides an opportunity to use smaller set of training data, they show that fine tuning outperforms training from scratch whos is preferable only when attempting new architectures,

So researchers usually propose fusing different architectures, which making different mistakes. Therefore, resulting in a smoother decision that makes less mistakes,

Data augmentation is used to bypass the need for data and to train a deep model with millions of parameters, by creates a myriad of new samples by applying random distortions (e.g., rotations, crops, resizes, color changes) to the existing samples and to get a stable model and easily result in overfitting.

III. Skin Lesion Segmentation Task

One of the most critical stages in the computerized study of melanoma is the accurate segmentation of skin lesions which is surrounded by healthy skin, Skin lesion segmentation is challenging due to a variety of factors, such as variations in skin tone, uneven illumination, border irregularity, shape symmetry, partial obstruction due to the presence of hair, low contrast between lesion and surrounding skin.

There exist different methods have been proposed in the literature for melanoma segmentation, based on active contours, region merging [17], histogram analysis methods and adaptive thresholding [18] or an hybrid methods that combine some algorithms were also exploited several times.

Skin lesion segmentation is the essential step for most classification approaches, in the past decades, researchers have developed various computer algorithms to conquer these challenges for example:

Esfahani et al. [19] proposed a new class of fully convolutional network, with new dense pooling layers for segmentation of lesion regions in non-dermoscopic images. Unlike other existing convolutional networks, this network is designed to produce dense feature maps and leads to highly accurate segmentation of lesions with dice score of 91.6%.

Jahanifar et al. [21] proposed a supervised saliency detection method to segment the lesions on dermoscopic images based on the discriminative regional feature integration (DRFI) algorithm [22] and used three different datasets ISBI2016 and ISBI2017 and PH2 dataset [52] .

Hongdiao Wen [23] proposed an II-FCN model for melanoma segmentation from dermoscopy image with several training methods, which overcomed overfitting problems of deep network. including data augmentaion, loss normalization, jaccard index, for better training the model. He build a symmetrical inception fully convolution network which are based on only 10 reversible inception blocks, every block composed of four convolution branches with combination of different layer depth and kernel size to extract sundry semantic features, the model used the ISBI 2017 dataset and achived jaccard index of 0.82.

Ramachandram et al. [24] presented new approach based on a FCNN architecture trained from scratch, for skin lesion segmentation trained network using nine convolution layer with varying strides 1 and 2. and also appling batch-normalization for the convolutional layers and using ReLu activations and a per-pixel cross-entropy loss function and Adam optimization [25], achieved a IOU score of 0.642.

Recently, Galdran et al. [26] proposed two deep convolutional neural networks for the segmentation and classification of skin lesion of the ISIC 2017 Challenge Skin Lesion Analysis - towards melanoma detection, focused on applying color constancy techniques to the training set in order to perform extensive data augmentation. Moreover the obtained segmentations were leveraged to improve the full image classification,

Yang et al. [29] presented a novel multi-task DCNN technique implemented based on the layout architectures of GoogleNet [27] and U-Net [28]. The proposed model used for the segmentation and classifications of different categories of lesion at the same time with an average value of Jaccard index for lesion segmentation is 0.724, while the average values of area under the receiver operating characteristic curve (AUC) on two individual lesion classifications are 0.880 and 0.972, respectively.

Yu et al. [30] proposed a novel method based on very deep CNNs using two steps: first construct a very deep fully convolutional residual network (more than 50 layers) , which incorporates multi-scale feature representations, to segment skin lesions, then classify them into melanoma ones and non-melanoma lesions.

Qi et al. [47] developed a new FCNN (less than 20 layers) using both local and global information to segment melanoma by adopting skipping layers to fuse multi-scale prediction maps from multiple layers, trained by images in the melanoma detection challenge 2017. Focused on residual network VGG 16 and discard its last two classification layers and replace all the fully connected layers by convolution layers with randomly initialized weights.

Attia et al. [48] proposed using a hybrid method that utilises deep convolutional and recurrent neural networks for skin lesion segmentation with an Auto encoder network consists of 7-convolutional layers with 2 max-pooling layers, then extracted feature maps are fed into 4 layers of recurrent network with 4 decoupled direction.

Li et al. [3] proposed two deep learning frameworks consisting of multi-scale fully-convolutional residual networks and addressing the three tasks of ISIC 2017, lesion segmentation, dermoscopic feature extraction and lesion classification. the first framework proposed is Lesion Indexing Network (LIN) based on FCRN-88 to simultaneously address lesion segmentation and lesion classification,it is trained with datasets using different data augmentation methods with proportionally resize the images to two scales 300x300 and 500x500, and unsing lesion index calculation unit (LICU) to refine the probabilities for Melanoma, Seborrheic keratosis and Nevus. the second framework proposed is Lesion Feature Network (LFN) to address dermoscopic feature extraction, based on CNN and trained by the patches extracted from the superpixel masks. this frameworks achieved AUC of 0.753 for segmentation, 0.912 for classification and 0.848 for dermoscopic feature extraction.

Vesal et al. [49] proposed a CNN-based skin lesion segmentation framework, which exploits both local and global image information, called SkinNet, this framework presented a modified version of U-Net [28], SkinNet employed two convolution layers with a kernel size of 3x3 in the lowest layer of the encoder branch, and encoded features was convolved with a different dilation rates of 1-32. Additionally, they replaced the conventional convolution layers in both the encoder and decoder branches with dense convolution blocks, that concatenated the feature maps from the previous layer with the current output feature map. also the input images was randomly augmented and resized to 512 x 512 pixels. SkinNet used the ISBI 2017 challenge dataset. and evaluated on the held-out challenge test data set, across 5-fold cross validation experiments. and achieved value of 85.10 for Dice coeffcient and 76.67 for Jaccard index and sensitivity of 93%.

Sarker, Md, et al. [50] proposed a novel deep learning skin lesion segmentation SLS model called SLSDeep, which based on training an encoder-decoder network. combining skip-connections, dilated residual and pyramid pooling networks.The encoder network without any pre- and post- processing algorithms constructed by dilated ResNet layers with downsampling, in turn the decoder depends on pyramid pooling network PPN followed by three convolution layers and upsampling. SLSDeep used a new loss function by combining both Negative Log Likelihood (NLL) and End Point Error (EPE) and the SLSDeep was evaluated on two public databases: ISBI 2016 and ISBI 2017 with different evaluation metrics: accuracy with 98,4% for ISBI 2016 and 93,6% for ISBI 2017, Dice coeffcient with 0.955 for ISBI 2016 and 0.878 for ISBI 2017, Jaccard index with 0.913 for ISBI 2016 and 0.782 for ISBI 2017.

IV. Skin Lesion Classification Task

Classification of dermoscopic images consist to produce a diagnostic about an input image and the distinction between the two classes (melanoma and benign) and assigns class labels 0 or 1 to data item by making inferences about the extracted information in the previous phases.

Lots of works was proposed in this task as Vasconcelos et al. [31] showed investigates how such a small and unbalanced biomedical dataset, based on the composition of CNN committees can be extended by data augmentations using a specialist knowledge image transforms (Color Augmentation and Geometric Augmentation) trained on the ISBI 2017 challenge dataset. for melanoma classification.

Chang [32] developed a novel deep learning based solution to solve melanoma classification problem, and achieve a very high melanoma prediction accuracy. In details he build a skin lesion segmentation neural network (skin_segnn), similar like U-Net architecture, then he build another deep neural network for the melanoma judgment, designed transfer learning based on Google inception v3 network (skin_recnn) that reduced the number of parameters in the network.

Diaz [33] presented a novel system for automatic diagnosis to solve classification problem of nevus, melanoma and seborrheic keratosis. with several networks providing lesion area identification, lesion segmentation into structural patterns and final diagnosis including data augmentation and convolutional neural networks (CNN).

Mirunaliniy et al. [34] developed an automated system for skin lesion classification using Google's pretrained CNN model known as Inception-v3 that consists of multiple convolution layers of filters of size 7x7, 3x3, 5x5, 1x1 and of varying strides 1 and 2. also pooling layers to reduce the size of the image. The system used two different neural networks with same representation vector, to detect the type of lesions as benign or malignant also the cause of the lesions either due to non-melanocytic or melanocytic cells. this model achieved an overall accuracy of 65.8% for the validation set.

Harangi [35] proposed an ensemble of deep convolutional neural networks (DCNNs) to classify dermoscopy images into three classes (melanoma, nevus, seborrheic keratosis) divided into two binary classification tasks between (melanoma, and nevus and seborrheic keratosis then between (seborrheic keratosis, nevus and melanoma) the approach concatenate the outputs of the softmax layers of four different deep convolutional neural networks architectures (DCNNs) considered the models GoogLeNet [36], AlexNet [36], ResNet[38], VGGNet [39] beside others. trained with augmented dataset, the final class label of an input image is derived as the majority of the ones provided by the individual DCNNs. this approach outperformed the accuracy of the individual DCNNs regarding skin lesions.

Menegola et al. [40] investigate how different transfer learning schemes influence automated melanoma classification results by training a DNN from scratch and differences between doing fine-tuning or not, and concluded that parametrization used for training the models and quality of the datasets needed an further investigation.

Murphree et al [41] proposed four distinct deep neural network approach with a transfer learning strategy, implemented three neural network architectures : deep convolutional neural network (CNN) trained from scratch, feature extractor using an ImageNet pre-trained Inception v3 network as a feature extractor to provide input for a multi-layer perceptron, fine tuning by using the best model found under the feature extractor, and an Hybrid architecture combine the fine tuning network from above with a multi-layer perceptron.

DeVries et al. [42] presented a multi-scale convolutional neural network which is fine-tuned for skin lesion classification, using an Inception-v3 network pre-trained with two different scales of input images, coarse scale that captures the overall context and shape characteristics and finer scale reveals textural details and low-level characteristics of the lesion for distinguishing between the classes of lesion.

Lopez et al. [43] presented a novel method to solve the problem of classifying a dermoscopic image containing a skin lesion as malignant or benign. particularly early melanoma detection, using an existing convolutional neural network (CNN) architecture – VGGNet and the transfer learning paradigm, in three different ways: training the ConvNet from scratch; using the transfer learning paradigm to leverage features from an existing convolutional neural network (CNN) architecture – VGGNet ; then keeping the transfer learning paradigm and fine-tuning the CNNs architecture, the proposed method achieves a sensitivity value of 78.66% and a precision of 79.74%.

Mishra et al. [44] used supervised classification of nine distinct dermatological diseases types by deep neural networks (DNN), trained on curated data. With human-level accuracies for few classes, explored popular pre-trained DNNs such as ResNet18, ResNet50, ResNet152 and DenseNet161, initialized on ImageNet, with two strategies for training and classification were evaluated. The first consisted of fine-tuning networks by freezing the network except for the final fully connected of these DNNs. The second approach was more rigorous by fine-tuning the entire network.

Mahbod et al. [46] presented deep feature extractor from different layers of the network using two pre-trained networks. AlexNet architecture and VGG-16 architecture; this model trained with skin lesion images available from the ISIC 2017 challenge, and achieved an AUC of 84.8% for Melanoma and AUC of 93.6% for seborrheic keratosis.

V. Skin Lesion Detection And Tracking Task

Li et al. [45] show a large-scale detection and tracking of skin lesion using FCNN trained with high volumes of synthetic data that merges 1,300 biopsied skin lesion images with 400 high resolution body images heavily augmented to generate 40,000 images for detection and 84,000 images for tracking, the detection system based on finetuned Google's Inception-V3 network architecture composed of a convolution section followed by deconvolutional section to generate a pialuaxel-wise heat-map over five classes to generate the region proposals then used its weights to initialize the tracking network whos evaluated using the percentage-of correct-key points (PCK) metric. this model outperforming both techniques SIFTFlow and Deformable Spatial Pyramids (DSP).

VI. Conclusion

This paper present a brief review of image analysis techniques for diagnosis of skin cancer specially for pigmented skin lesions using deep learning techniques based convolutional neural network. The aim of this review is to give an important contribution to this research area and to summarize the continuous emergence of new techniques for dermoscopic image analysis in the recent years, by analysing of various papers with respect to several criteria, such as Transfer learning, and hybridation of different architectures, Data augmentation. This paper reviewed a study that combines the research being done related to all the steps needed for developing an automatic diagnostic system for skin cancer including segmentation; classification; detection and tracking.

TABLE I. Summarized different models in the literature for skin lesion segmentation

References	Year	Comments	Database
Li et al. [3]	2018	Lesion Indexing Network (LIN) based on FCRN-88 Lesion Feature Network (LFN) based on CNN	ISBI 2017
Esfahani et al. [19]	2017	FCN and dense pooling layers	Dermquest [20]
Jahanifar et al [21]	2018	Discriminative regional feature integration (DRFI)	ISBI2016 ISBI2017 PH2 [51]
Hongdiao Wen [23]	2017	FNC based on only 10 reversible inception blocks	ISBI 2017
Ramachandram et al. [24]	2017	FCNN architecture trained from scratch with 9 -convolutional layers	ISBI 2017
Galdran et al. [26]	2017	DCNN with Color Augmentation Techniques	ISBI 2017
Yang et al. [29]	2017	DCNN technique implemented based on the layout architectures of GoogleNet and U-Net	ISBI 2017
Yu et al. [30]	2017	Deep fully convolutional residual network(more than 50 layers)	ISBI 2016
Qi et al. [47]	2017	FCNN (less than 20 layers) with local and global information focused on residual network VGG 16	ISBI 2017
Attia et al. [48]	2017	Hybrid method that use deep convolutional and RNN and an Auto encoder network with 7-convolutional layers	ISBI 2017
Vesal et al. [49]	2018	CNN with modified version of U-Net exploits both local and global image information	ISBI 2017
Sarker, Md, et al. [50]	2018	Encoder-decoder network. combining skip-connections, dilated residual and pyramid pooling networks	ISBI 2016 ISBI 2017

TABLE II. Summarized different models in the literature for skin lesion classification

References	Year	Comments	Database
Vasconcelos et al. [31]	2017	CNN topology and hyper-parameters from GoogLeNet	ISBI 2017
Chang [32]	2017	Skin_segnn based on U-Net architecture, Skin_recnn based on Google inception v3 network	ISBI 2017
Diaz [33]	2017	Fully Convolutional Network	ISBI 2016
Mirunaliniy et al [34]	2017	CNN model known as Inception-v3 using Google's inspection model.	ISBI 2017
Harangi [35]	2017	Different deep convolutional neural networks architectures (DCNNs) considered the models GoogLeNet, AlexNet, ResNet,VGGNet	ISBI 2017
Menegola et al. [40]	2016	DNN from scratch based VGG- model	dermatology Atlas
Murphree et al. [41]	2017	Deep convolutional neural network (CNN) trained from scratch and feature extractor using pre-trained Inception v3	ISBI 2017
DeVries et al. [42]	2017	Multi-scale convolutional neural network using an Inception-v3 network	ISBI 2017
Lopez et al. [43]	2017	Convolutional neural network (CNN) architecture based VGGNet	ISBI 2017
Mishra et al. [44]	2018	Deep neural networks (DNN by explored popular pre-trained DNNs such as ResNet18, ResNet50, ResNet152, DenseNet161	Dataset of 9 diseases from 150,000 images
Mahbod et al [46]	2017	DCNN using two pre-trained networks. AlexNet architecture and VGG-16 architecture	ISBI 2017

References

[1] https://www.skincancer.org/skin-cancer-information

[2] J. March, M. Hand, D. Grossman, Practical application of new technologies for melanoma diagnosis: Part 1. Noninvasive approaches. J Am Acad Dermatol., 72(6), 929- 41, 2015.

[3] Yuexiang Li, Linlin Shen, "Skin Lesion Analysis towards Melanoma Detection Using Deep Learning Network",11 Feb 2018.

[4] American Cancer Society, "Cancer Facts & Figures 2016," American Cancer Society, Atlanta, GA, USA, 2016.

[5] https://www.medicalnewstoday.com/articles/154322.php.

[6] Mohammad H. Jafari, Ebrahim Nasr-Esfahani, Nader Karimi, S.M. Reza Soroushmehr, Shadrokh Samavi, Kayvan Najarian "Extraction of Skin Lesions from Non-Dermoscopic Images Using Deep Learning", 2016.

[7] G. Argenziano, G. Fabbrocini, P. Carli, V. De Giorgi, E. Sammarco, and M. Delfino, "Epiluminescence microscopy for the diagnosis of doubtful melanocytic skin lesions: comp. of the abcd rule of dermatoscopy and a new 7-point checklist based on pattern analysis," Archives of Dermatology, vol. 134, no. 12, pp. 1563-1570, 1998.

[8] M. Vestergaard, P. Macaskill, P. Holt, and S. Menzies, "Dermoscopy compared with naked eye examination for the diagnosis of primary melanoma: a meta-analysis of studies performed in a clinical setting," Br. J. Dermatol., vol. 159, no. 3, pp. 669–676, 2008.

[9] https://isic-archive.com/

[10] [10] https://challenge2018.isic-archive.com/

[11] [11] Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. «ImageNet classification with deep convolutional neural networks.» Advances in neural information processing systems. 2012.

[12] Simonyan, Karen, and Andrew Zisserman. «Very deep convolutional networks for large-scale image recognition.»,2014.

[13] Szegedy, Christian, et al. «Going deeper with convolutions.» Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2015.

[14] He, Kaiming, et al. «Deep residual learning for image recognition.» Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2016.

[15] Huang, Gao, et al. «Densely connected convolutional networks.» 2016.

[16] Sabour, Sara, Nicholas Frosst, and Geoffrey E. Hinton. «Dynamic routing between capsules.» Advances in Neural Information Processing Systems. 2017.

[17] M. E. Celebi et al., "Border detection in dermoscopy images using statistical region merging," Ski. Res. Technol., vol. 14, no. 3, pp. 347-353, 2008.

[18] M. E. Celebi, H. Iyatomi, G. Schaefer, and W. V Stoecker, "Lesion border detection in dermoscopy images," Comput. Med. Imaging Graph, vol. 33, no. 2, pp. 148-153, 2009.

[19] E. Nasr-Esfahani, S. Rafiei, Mohammad H. Jafari, Nader Karimi, James S. Wrobel, Kayvan Najarian, Shadrokh Samavi, S.M. Reza Soroushmehr, "Dense Fully Convolutional Network for Skin Lesion Segmentation", 2017.

[20] Vision and Image Processing Lab, [Online]. Available: http://vip.uwaterloo.ca/demos/skin-cancer-detection. Accessed on: 29 October, 2017.

[21] Mostafa Jahanifar, Neda Zamani Tajeddin, Babak Mohammadzadeh Asl, Ali Gooya,"Supervised Saliency Map Driven Segmentation of the Lesions in Dermoscopic Images",Special Issue on "Skin Lesion Image Analysis for Melanoma Detection", 7 Jun 2018.

[22] F. Peruch, F. Bogo, M. Bonazza, V.-M. Cappelleri, and E. Peserico,"Simpler, faster, more accurate melanocytic lesion segmentation throughmeds," IEEE Trans. Biomed. Eng., vol. 61, no. 2, pp. 557–565, 2014.

[23] Hongdiao Wen, "II-FCN for skin lesion analysis towards melanoma detection" Chengdu,China, 14 Mar 2017.

[24] Dhanesh Ramachandram,Terrance DeVries," LesionSeg: Semantic segmentation of skin lesions using Deep Convolutional Neural Network", 15 Mar 2017.

[25] Diederik Kingma and Jimmy Ba. Adam: " A method for stochastic optimization.", 2014.

[26] Adrian Galdran, Aitor Alvarez-Gila, Maria Ines Meyer, Cristina L. Saratxaga, Teresa Araújo, Estibaliz Garrote, Guilherme Aresta, Pedro Costa, A.M. Mendonça, Aurélio Campilho,"Data-Driven Color Augmentation Techniques for Deep Skin Image Analysis", 10 Mar 2017.

[27] Christian Szegedy, Wei Liu,Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, Andrew Rabinovich, «Going deeper with convolutions", 17 Sep 2014.

[28] O. Ronneberger, P. Fischer, and T. Brox, U-net: Convolutional networks for biomedical image segmentation, in MICCAI 2015, pp. 234–241, Springer, 2015.

[29] Xulei Yang, Zeng Zeng, Si Yong Yeo, Colin Tan, Hong Liang Tey, Yi Su, "A Novel Multi-task Deep Learning Model for Skin Lesion Segmentation and Classification", 3 Mar 2017.

[30] Lequan Yu, Hao Chen, , Qi Dou, Jing Qin, Pheng-Ann Heng, "Automated Melanoma Recognition in Dermoscopy Images via Very Deep Residual Networks", IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 36, NO. 4, APRIL 2017.

[31] Cristina Nader Vasconcelos, Bárbara Nader Vasconcelos , "Convolutional neural network committees for melanoma classification with classical and expert knowledge based image transforms data augmentation",15 Mar 2017.

[32] Hao Chang, " Skin cancer reorganization and classification with deep neural network", 2017.

[33] Iván González-Díaz,"Incorporating the Knowledge of Dermatologists to Convolutional Neural Networks for the Diagnosis of Skin Lesions" ,2 Jun 2017.

[34] P. Mirunaliniy, Aravindan Chandrabose y, Vignesh Gokul y, S. M. Jaisakthi , "Deep Learning for Skin Lesion Classification", 13 Mar 2017.

[35] Balazs Harangi, "skin lesion detection based on an ensemble of deep convolutional neural networks", May 2017.

[36] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. E. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, A, Rabinovich. "Going deeper with convolutions", 2014.

[37] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks", In Advances in neural information processing systems, pp. 1097–1105, 2012.

[38] K. He, X. Zhang, S. Ren, J. Sun, "Deep Residual Learning for Image Recognition", 2015.

[39] K. Simonyan, and A. Zisserman, "Very deep convolutional networks for large-scale imagerecognition", 2014.

[40] Afonso Menegola, Michel Fornaciali, Ramon Pires, Sandra Avila, Eduardo Valle,"Towards Automated Melanoma Screening: Exploring Transfer Learning Schemes", 5 Sep 2016.

[41] Dennis H. Murphree, Mayo Clinic, Che Ngufor ,"Transfer Learning for Melanoma Detection: Participation in ISIC 2017 Skin Lesion Classification Challenge", 2017.

[42] Terrance DeVries ,Dhanesh Ramachandram, "Skin Lesion Classification Using Deep Multi-scale Convolutional Neural Networks", 4 Mar 2017.

[43] Adria Romero Lopez, Xavier Giro-i-Nieto, Jack Burdick, Oge Marques, "skin lesion classification from dermoscopic images using deep learning techniques",Biomedical Engineering, 2017.

[44] Sourav Mishra, Toshihiko Yamasaki, Hideaki Imaizumi, Supervised classification of dermatological diseases via Deep learning", 17 May 2018.

[45] Yunzhu Li, Andre Esteva, Brett Kuprel, Rob Novoa, Justin Ko, Sebastian Thrun,"Skin Cancer Detection and Tracking Using Data Synthesis and Deep Learning", 4 Dec 2016.

[46] Amirreza Mahbod, Rupert Ecker, and Isabella Ellinger , "Skin Lesion Classification Using Hybrid Deep Neural Networks",2017

[47] Jin Qi, Miao Le, Chunming Li and Ping Zhou ,"global and local information based deep network for skin lesion segmentation", 16 Mar 2017.

[48] M. Attia, M. Hossny, S. Nahavandi, A. Yazdabadiy, "Spatially Aware Melanoma Segmentation Using Hybrid Deep Learning Techniques", March 2, 2017.

[49] Sulaiman Vesal, Nishant Ravikumar and Andreas Maier, "SkinNet: A Deep Learning Framework for Skin Lesion Segmentation", 25 Jun 2018.

[50] Md. Mostafa Kamal Sarker, Hatem A. Rashwan , Farhan Akram, Syeda Furruka Banu, Adel Saleh, Vivek Kumar Singh, Forhad U H Chowdhury, Saddam Abdulwahab, Santiago Romani, Petia Radeva, Domenec Puig, «SLSDeep: Skin Lesion Segmentation Based on Dilated Residual and Pyramid Pooling Networks.», 31 May 2018.

[51] T. Mendonça, P. M. Ferreira, J. S. Marques, A. R. S. Marcal, and J. Rozeira, "PH2 - A dermoscopic image database for research and benchmarking," in 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2013, pp. 5437– 5440.