Convolutional Neural Networks for Classifying Melanoma Images

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ABSTRACT

In this work, we address the problem of skin cancer classification using convolutional neural networks. A lot of cancer cases early on are misdiagnosed as something else leading to severe consequences including the death of a patient. Also there are cases in which patients have some other problems and doctors think they might have skin cancer. This leads to unnecessary time and money spent for further diagnosis. In this work, we address both of the above problems using deep neural networks and transfer learning architecture. We have used publicly available ISIC databases for both training and testing our model. Our work achieves an accuracy of 0.935, precision of 0.94, recall of 0.77, F1 score of 0.85 and ROC- AUC of 0.861 which is better than the previous state of the art approaches.

Keywords: Convolutional Neural Network (CNN), transfer learning, classification, Residual neural network (RELU), Adam Optimizer

1. Introduction

Skin cancer is the most widespread cancer diagnosed in the world. It is seen that if it can be diagnosed in its early phases, with choosing the appropriate treatment, survival rates are very good. Hence it is absolutely necessary to get to know at the earliest whether the symptoms of the patient correspond to cancer or not. Traditionally, doctors have been using their naked eye for skin cancer detection. However on many occasions this leads to not so accurate detection as people make mistakes. Even experts have a tough time saying it, especially when the cancer is at the very early stages. This is where computer vision can help in automating the whole pipeline. A deep neural network can be trained on thousands of images of both the categories i.e. benign and malignant. By learning the non linear interactions, the model can iself tell whether a new image corresponds to a benign or malignant class. This automation could not only have a higher efficiency in avoiding both false positives and false negatives but also reduce time and manual spent on more productive work. Our model can be deployed on places which lack expert doctors. This work could dramatically change the healthcare and well being of humans in developing countries of Asia and Africa.

2. Existing Work

There has been a lot of work published in the domain of skin cancer classification using deep learning and computer vision techniques. These works use a lot of different approaches including classification only, segmentation and detection, image processing using different types of filters etc.

Almansour et al. [5] developed an algorithm for the classification of melanoma by using k-means clustering, and Support Vector Machine (SVM). [7] separately used AdaBoost to classify skin lesions. [9], and [10] used different sets of features including type of lesion, texture, colour etc and neural networks for the making of a robust diagnosis system. [21] developed an algorithm for diagnosis of melanoma. The examples till now only showed algorithms using traditional machine learning techniques, but lately deep learning have proved to be more accurate. The reason is that it automates the feature extraction process completely. It is upto the algorithms to find the better features and train the model accordingly. In [22], Esteva et al. made a breakthrough on skin cancer classification by a pre-trained GoogleNet Inception v3 CNN model to classify 129,450 clinical skin cancer images including 3,374 dermatoscopic images. [23] developed a convolutional neural network with over 50 layers on ISBI 2016 challenge dataset for the classification of malignant melanoma. In 2018, [24] utilized a deep convolutional neural network to classify a binary class problem of dermoscopy images. [25] developed an algorithm using Support Vector Machines combined with a deep convolutional neural network approach for the classification of 4 diagnostic categories of clinical skin cancer images. [26] used a deep convolutional neural network to classify the clinical images of 12 skin diseases.

Our work builds on the aforementioned approaches. In this paper we have tackled skin cancer classification which is of binary type i.e. there are 2 classes present in the dataset benign and malignant. We have used the publicly available ISIC database for both training and testing the images. We have compared 5 backbone transfer learning architectures - VGG16, ResNet50, InceptionV3, MobileNet and DesneNet169. We have used familiar metrics for evaluating our results including confusion metric. Since there are equal numbers of images in both the classes, hence accuracy alone should be a good enough metric. Nevertheless we present other matric results including precision, recall, F1 score and ROC-AUC. Our work achieves an accuracy of 0.935, precision of 0.94, recall of 0.77, F1 score of 0.85 and ROC-AUC of 0.861 which is better than the previous state of the art approaches.

2.1 Image Classification

There are various image classification approaches which can be categorized under two heads - First one uses traditional machine learning algorithms like Decision Tree, Support Vector Machines, Fuzzy Measures etc and the other is based on deep learning like convolutional neural networks, autoencoders etc. Other than Artificial Neural Networks (ANNs), methods Decision Trees, Support Vector Machines, and Fuzzy Measures have been used.

Decision Trees is a machine learning method that works by calculating a class membership, which is done by partitioning a dataset into subsets repeatedly. This hierarchical classification permits approval and elimination of class labels at each stage. This method as a whole, has 3 major steps: Partition the nodes using the dataset, find all the terminal nodes, and allocate class labels to each terminal node. Support Vector Machines are used for a variety of machine learning applications. They work by building a hyper-plane or a set of hyper-planes, in a high-dimensional space. Good separation and classification is achieved when a hyper-plane has the largest distance to the nearest point of any class. Fuzzy measures another classification technique used. Multiple varied stochastic associations are determined in order to

describe the image characteristics. The difference stochastic associations are then combined to form a set of properties.

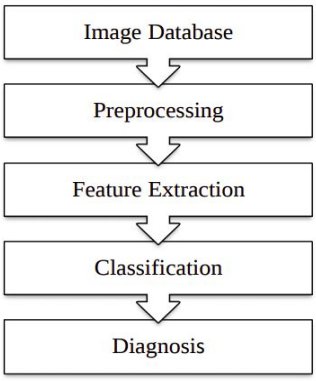

Fig 1. General steps for any image classification application

2.2 Deep Learning

Deep learning is a set of machine learning methods that was inspired by information processing and distributed communication in networks of biological neurons. Deep learning predominantly involves development, training and utilization of artificial neural networks (ANNs). ANNs are networks of artificial neurons that are based on biological neurons. Every ANN has at least 3 layers: an input layer that takes the input, a hidden layer that trains on the dataset fed to the input layer, and an output layer that gives an output depending on the application.

Deep learning has been gaining wide acclaim because of the results it achieves that have never been seen in any other machine learning method. Convolutional Neural Networks (a type of ANNs), are extensively used for image-based applications, and have achieved better results than humans in object detection and classification.

2.3 Convolutional Neural Networks

CNNs are a kind of neural network which have proven to be very powerful in areas such as image recognition and classification. CNNs can identify faces, pedestrians, traffic signs and other objects better than humans and therefore are used in real time applications like robots and self-driving cars.

CNNs are a supervised learning method and are trained using labeled data given with the respective classes. CNNs learn the relationship between the input objects and the class labels and comprise two components: the hidden layers in which the features are extracted and, at the end of the processing, the fully connected layers that are used for the actual classification task. The hidden layers of CNN have a specific architecture consisting of convolutional layers, pooling layers and activation functions for switching the neurons either on or off. In a typical neural network, each layer is formed by a set of neurons and one neuron of a layer is connected to each neuron of the preceding layer while the architecture of hidden layers in CNN is slightly different. The neurons in a layer are not connected to all neurons of the preceding layer; rather, they are connected to only a small number of neurons from the previous layer. This restriction to local connections and additional pooling layers summarizing local

neuron outputs into one value results in translation-invariant features. This results in a simpler training procedure due to less parameters and a lower model complexity.

2.4 Skin Cancer Classification

A number of factors can make skin cancer recognition a challenging task. Some of these factors include flaws in image quality like uneven brightness, obstruction, and also the fact that there are many images which have similar shape, color and texture.

2.5 DATASET

We obtained a public dataset from ISIC website for skin cancer classification. We used the ISIC Archive Downloader to download the images. We used 3000 images for training and 600 images for validation of size 224 × 224. The images are distributed equally between training and validation sets which are shown below in Fig 2 and Fig 3.

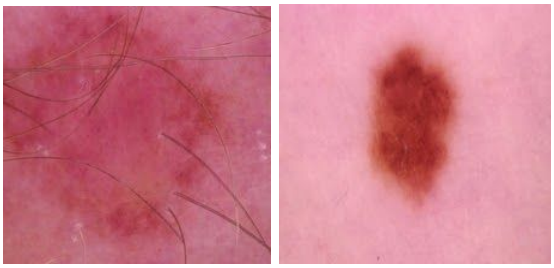

Fig 2. Benign images

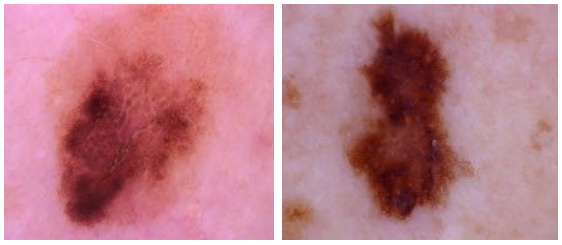

Fig 3. Malignant images

3. PROPOSED METHOD

We have used the concept of transfer learning for the classification. With transfer learning, instead of starting the learning process from scratch, the model starts from patterns that have been learned when solving a different problem. This way the model leverages previous learnings and avoids starting from scratch. In image classification, transfer learning is usually expressed through the use of pre-trained models. A pre-trained model is a model that was trained on a large benchmark dataset to solve a problem similar to the one that we want to solve. We used three pre-trained models- Inception v3, InceptionResNet v2 and ResNet 152 as the pre trained weights for our work.

3.1 Inception v3

Google's Inception v3 architecture was re-trained on our dataset by fine-tuning across all layers and replacing top layers with one average pooling, two fully connected and finally the softmax layer allowing to classify 2 diagnostic categories. The size of input images was all resized to (224, 224) to be compatible with this model. Learning rate was set to 0.0001 and Adam was used for the optimizer.

3.2 InceptionResNet v2

InceptionResNet v2 architecture was re-trained on our dataset by fine-tuning across all layers and replacing top layers with one global average pooling, one fully connected and finally the softmax layer allowing to classify 2 diagnostic categories. The size of input images was all resized to (224, 224) to be compatible with this model. Learning rate was set to 0.0001 and Adam was used for the optimizer.

3.3 ResNet50

ResNet 50 architecture was re-trained on our dataset by fine-tuning across all layers and replacing top layers with one average pooling, one fully connected and finally the softmax layer allowing to classify 2 diagnostic categories. The size of input images was all resized to (224, 224) to be compatible with this model. Learning rate was set to 0.0001 and Adam was used for the optimizer. It uses identity mapping to map the inputs. This identity mapping does not have any parameters and is just there to add the output from the previous layer to the layer ahead. The identity mapping is multiplied by a linear projection W to expand the channels of shortcut to match the residual. The Skip Connections between layers add the outputs from previous layers to the outputs of stacked layers. This results in the ability to train much deeper networks than what was previously possible.

3.4 MobileNet

The fundamental part of MobileNet is depthwise separable filters, named as Depthwise Separable Convolution. These convolutions layers which is a form of factorized convolutional factorize a standard convolution into a depthwise convolution called a pointwise convolution. In MobileNet, the depthwise convolution applies a single filter to each input channel. The pointwise convolution then applies the convolution operation to combine the outputs of the depthwise convolution.

3.5 DenseNet169

To solve the vanishing gradient problem, this architecture uses a simple connectivity pattern to ensure the maximum flow of information between layers both in forward and backward computation. The layers are connected in a way such that inputs from all preceding layers passes through its own feature-maps to all subsequent layers. To facilitate the down-sampling in the architecture, the entire architecture is divided into multiple densely connected blocks. The layers between these dense blocks are transition layers which perform convolution and pooling operations.

3.6 Transfer Learning

Transfer learning is a popular method in computer vision that allows us to build accurate models faster. With transfer learning, instead of starting the learning process from scratch, we start from patterns that have been learned when solving a different problem.

The advantages of using transfer learning are:

1. Super simple to incorporate.
2. Achieve the same or even better(depending on the dataset) model performance quickly.
3. There's not as much labeled data required.
4. Versatile uses cases from transfer learning, prediction, and feature extraction.

The proposed method can be summarized in the following seven points:

1. We split the dataset into two parts-training set and test set with 80% and 20% images respectively.

2. We used data augmentation like shearing, zooming, flipping and brightness change to increase the dataset size to almost double the original dataset size.

3. We tried with pre trained models like Inception v3, InceptionResNet v2, ResNet 50, MobileNet and DenseNet169 by fine tuning the last few layers of the network.

4. We used 50% dropout and batch normalization layers in between to reduce overfitting.

5. We used two dense layers with 64 neurons and 2 neurons respectively. The last layer is used for the classification with softmax as the activation function.

6. We used binary cross entropy as the loss function.

7. We trained the model for 20 epochs with a batch size of 32 by changing the hyper-parameters like learning rate, batch size, optimizer and pre-trained weights.

4. EXPERIMENTAL RESULTS

In this section we present our findings. We plotted the loss vs epochs, accuracy vs epochs, confusion matrix for the classifier and ROC-AUC curve for the classifier. The plots are shown in Fig 4 with details of experiment in Table 1.

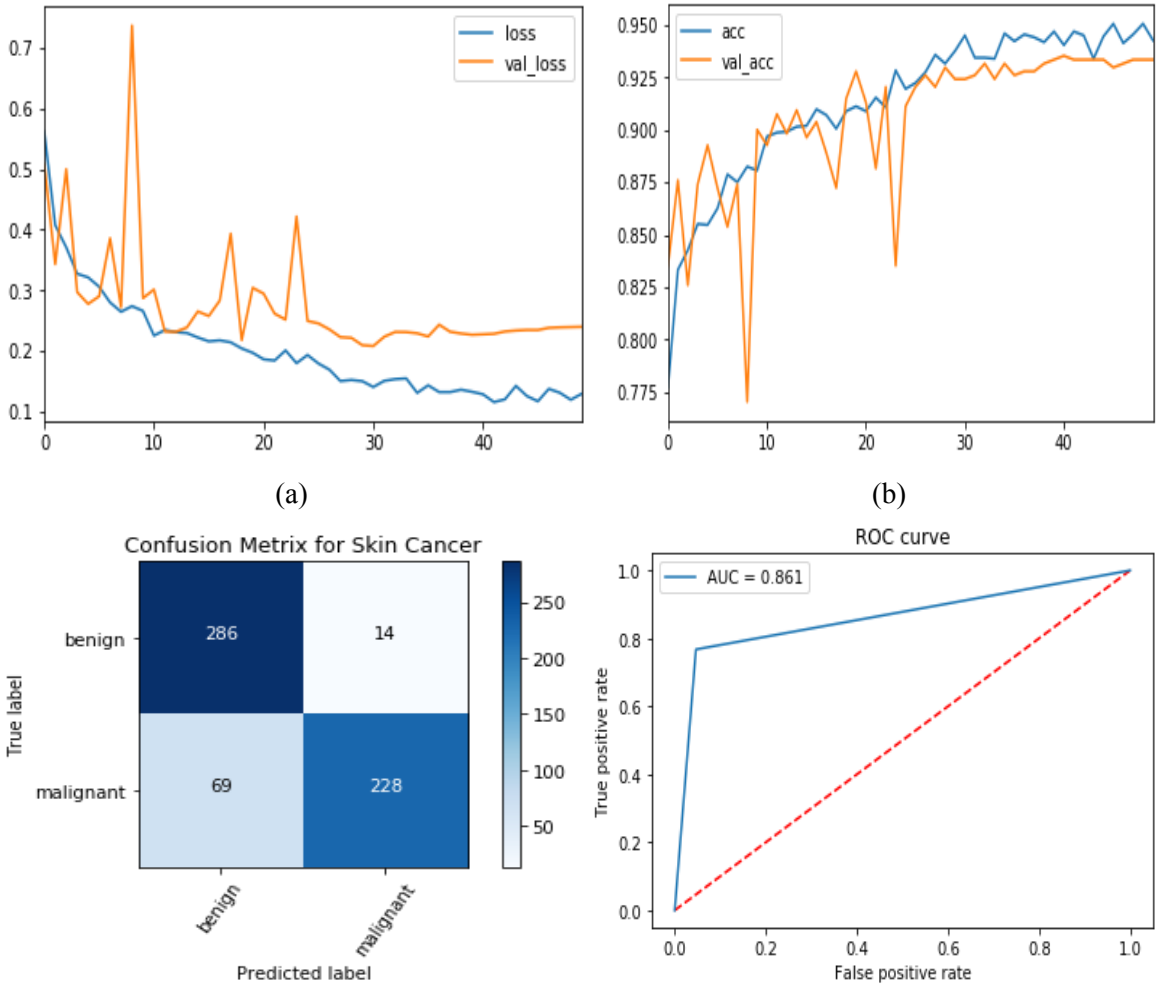

Fig 4. a) Loss vs epoch b) Accuracy vs epoch c) Confusion Matrix d) ROC-AUC curve

Table 1. Precision, recall F1 score values

	precision	recall	F1 score
300	0.94	0.77	0.85
600	0.87	0.86	0.86

Next, we present our findings and show the validation of our trained models. In this paper, two types of major skin cancer categories are used. The evaluation and results of trained models is calculated by common classification metrics which are defined as follows:

The output of a binary classifier is interpreted as a probability distribution over the classes. Normally, objects with an output value greater than .5 are assigned to the positive class in a binary classifier and objects with an output value less than .5 are assigned to the negative class. An alternative approach is used based on the receiver operating characteristic (ROC). The threshold used for classification systematically varies between 0 and 1, and the sensitivity and specificity are determined for each selected threshold. The ROC curve is calculated by plotting the sensitivity against 1-specificity and can be used to evaluate the classifier. The further the ROC curve deviates from the diagonal, the better the classifier. A suitable overall measure for the curve is the area under the curve (AUC).

Table 2. Effect of batch size on results

Batch size	Accuracy	Precision	Recall	F1 score	ROC-AUC
32	0.928	0.91	0.74	0.82	0.844
64	**0.935**	**0.94**	**0.77**	**0.85**	**0.861**

We found that a batch size value of 64 gives better results when compared to that of 32.

Table 3. Effect of learning rate on results

Learning Rate	Accuracy	Precision	Recall	F1 score	ROC-AUC
0.0001	**0.935**	**0.94**	**0.77**	**0.85**	**0.861**
0.00001	0.915	0.88	0.72	0.79	0.813

Table 4. Comparison of Adam vs SGD as optimizer

Optimizer	Accuracy	Precision	Recall	F1 score	ROC-AUC
Adam	**0.935**	**0.94**	**0.77**	**0.85**	**0.861**
SGD	0.903	0.92	0.71	0.80	0.830

We found that Adam as an optimizer performed better than Stochastic Gradient Descent (SGD) with momentum decay.

Table 5. Comparison of pre trained weights on results.

Pre trained weights	Accuracy	Precision	Recall	F1 score	ROC-AUC
ResNet50	**0.935**	**0.94**	**0.77**	**0.85**	**0.861**
InceptionV3	0.893	0.92	0.71	0.80	0.839
Inception ResNet v2	0.907	0.90	0.70	0.79	0.839
MobileNet	0.884	0.92	0.74	0.82	0.824
Densenet169	0.903	0.93	0.73	0.82	0.847

We found that ResNet152 as the backbone gives better results when compared to InceptionV3, InceptionResNetV2, Mobilenet and Densenet169.

Table 6. Comparison with previous work

	Accuracy (%)	ROC-AUC
Pomponiu et al [27]	93.64	-
Gutman et al [28]	93.1	-
Haenssle et al [29]	-	0.86
Han et al [30]	-	0.83
Bi et al [31]	-	0.915
Kawahara et al [32]	79.5	-
Lopez et al [33]	81.33	-
Nasr-Esfahani et al [34]	81	-
Ours	**93.5**	**0.861**

The comparison with previous state of the art results is shown in Table 6. Pomponiu et al achieves a higher accuracy as they have used the complete dataset. Since our objective was to show comparable results with limited images, hence our accuracy is good enough considering the number of images on which our model is trained. Bi et al has much better ROC-AUC than ours as they have used an ensemble of CNNs for training, rather than ours which only used a single CNN architecture. Other than that our work archives state of the art results on skin cancer classification.

5. CONCLUSION

In conclusion, this study investigated the ability of deep convolutional neural networks in the classification of benign vs malignant skin cancer. Our results show that state-of-the-art deep learning architectures trained on dermoscopy images (3600 in total composed of 3000 training and 600 validation) outperforms dermatologists. We showed that with use of very deep convolutional neural networks using transfer learning and fine-tuning them on dermoscopy images, better diagnostic accuracy can be achieved compared to expert physicians and clinicians. Although no preprocessing step is applied in this paper, the experimental results are very promising. These models can be easily implemented in dermoscopy systems or even on smartphones in order to assist dermatologists. More diverse datasets (varied categories, different ages) with much more dermoscopy images and balanced samples per class is needed for further improvement. Also using the metadata of each image can be useful to increase the accuracy of the model.

5. REFERENCES

[1] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. Advances in neural information processing systems (pp. 1097-1105).

[2] L. Yu, H. Chen, Q. Dou, J. Qin, and P.-A. J. I. t. o. m. i. Heng, "Automated melanoma recognition in dermoscopy images via very deep residual networks," vol. 36, no. 4, pp. 994-1004, 2017.

[3] G. Litjens et al., "A survey on deep learning in medical image analysis," vol. 42, pp. 60- 88, 2017.

[4] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely Connected Convolutional Networks," in CVPR, 2017, vol. 1, no. 2, p. 3.

[5] U.-O. Dorj, K.-K. Lee, J.-Y. Choi, M. J. M. T. Lee, and Applications, "The skin cancer classification using deep convolutional neural networks," pp. 1-16, 2018.

[6] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich. Going deeper with convolutions. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition,pages 1–9,2015.

[7] A. Esteva et al., "Dermatologist-level classification of skin cancer with deep neural networks," vol. 542, no. 7639, p. 115, 2017.

[8] K. He, X. Zhang, S. Ren, and J. Sun. Identity Mappings in Deep Residual Networks. arXiv preprint arXiv:1603.05027v3,2016.

[9] Xu, L., Ren, J. S., Liu, C., & Jia, J. (2014). Deep convolutional neural network for image deconvolution. In Advances in neural information processing systems (pp. 1790-1798).

[10] Qayyum, A., Anwar, S. M., Awais, M., & Majid, M. (2017). Medical image retrieval using deep convolutional neural network. Neurocomputing, 266, 8-20.

[11] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. arXiv preprint arXiv:1512.03385,2015.

[12] Kamavisdar, P., Saluja, S., & Agrawal, S. (2013). A survey on image classification approaches and techniques. International Journal of Advanced Research in Computer and Communication Engineering, 2(1), 1005-1009.

[13] Agarap, A. F. (2018). Deep learning using rectified linear units (relu). arXiv preprint arXiv:1803.08375.

[14] Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014). Dropout: a simple way to prevent neural networks from overfitting. The journal of machine learning research, 15(1), 1929-1958.

[15] Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.

[16] Noel Codella, Veronica Rotemberg, Philipp Tschandl, M. Emre Celebi, Stephen Dusza, David Gutman, Brian Helba, Aadi Kalloo, Konstantinos Liopyris, Michael Marchetti, Harald Kittler, Allan Halpern: "Skin Lesion Analysis Toward Melanoma Detection 2018: A Challenge Hosted by the International Skin Imaging Collaboration (ISIC)", 2018;

[17] A. Veit, M. Wilber and S. Belongie. Residual Networks Behave Like Ensembles of Relatively Shallow Networks. arXiv:1605.06431v2,2016.

[18] Tschandl, P., Rosendahl, C. & Kittler, H. The HAM10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions. *Sci. Data* **5**, 180161 doi:10.1038/sdata.2018.161 (2018).

[19] G. Huang, Z. Liu, K. Q. Weinberger and L. Maaten. Densely Connected Convolutional Networks. arXiv:1608.06993v3,2016.

[20] G. Huang, Y. Sun, Z. Liu, D. Sedra and K. Q. Weinberger. Deep Networks with Stochastic Depth. arXiv:1603.09382v3,2016.

[21] Esteva, Andre, et al. "Dermatologist-level classification of skin cancer with deep neural networks." *Nature* 542.7639 (2017): 115-118.

[22] Liao, Haofu. "A deep learning approach to universal skin disease classification." *University of Rochester Department of Computer Science, CSC* (2016).

[23] Dorj, Ulzii-Orshikh, et al. "The skin cancer classification using deep convolutional neural networks." *Multimedia Tools and Applications* 77.8 (2018): 9909-9924.

[24] Brinker, Titus Josef, et al. "Skin cancer classification using convolutional neural networks: systematic review." *Journal of medical Internet research* 20.10 (2018): e11936.

[25] Rezvantalab, Amirreza, Habib Safigholi, and Somayeh Karimijeshni. "Dermatologist level dermoscopy skin cancer classification using different deep learning convolutional neural networks algorithms." *arXiv preprint arXiv:1810.10348* (2018).

[26] Codella, Noel CF, et al. "Deep learning ensembles for melanoma recognition in dermoscopy images." *IBM Journal of Research and Development* 61.4/5 (2017): 5-1.

[27] Pomponiu, V., Nejati, H., & Cheung, N. M. (2016, September). Deepmole: Deep neural networks for skin mole lesion classification. In *2016 IEEE International Conference on Image Processing (ICIP)* (pp. 2623-2627). IEEE.

[28] Codella, N. C., Gutman, D., Celebi, M. E., Helba, B., Marchetti, M. A., Dusza, S. W., ... & Halpern, A. (2018, April). Skin lesion analysis toward melanoma detection: A challenge at the 2017 international symposium on biomedical imaging (isbi), hosted by the international skin imaging collaboration (isic). In 2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018) (pp. 168-172). IEEE.

[29] Haenssle, H. A., Fink, C., Schneiderbauer, R., Toberer, F., Buhl, T., Blum, A., ... & Uhlmann, L. (2018). Man against machine: diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists. *Annals of Oncology*, *29*(8), 1836-1842.

[30] Han, S. S., Kim, M. S., Lim, W., Park, G. H., Park, I., & Chang, S. E. (2018). Classification of the clinical images for benign and malignant cutaneous tumors using a deep learning algorithm. *Journal of Investigative Dermatology*, *138*(7), 1529-1538.

[31] Bi, L., Kim, J., Ahn, E., & Feng, D. (2017). Automatic skin lesion analysis using large-scale dermoscopy images and deep residual networks. *arXiv preprint arXiv:1703.04197*.

[32] Kawahara, J., & Hamarneh, G. (2016, October). Multi-resolution-tract CNN with hybrid pretrained and skin-lesion trained layers. In *International workshop on machine learning in medical imaging* (pp. 164-171). Springer, Cham.

[33] Lopez, A. R., Giro-i-Nieto, X., Burdick, J., & Marques, O. (2017, February). Skin lesion classification from dermoscopic images using deep learning techniques. In *2017 13th IASTED international conference on biomedical engineering (BioMed)* (pp. 49-54). IEEE.

[34] Nasr-Esfahani, E.,amavi, S., Karimi, N., Soroushmehr, S. M. R., Jafari, M. H., Ward, K., & Najarian, K. (2016, August). Melanoma detection by analysis of clinical images using convolutional neural networks. In *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)* (pp. 1373-1376). IEEE.