A DEEP LEARNING APPROACH FOR CLASSIFICATION OFSKIN CANCER DISEASE

Bangaru Siva Kumar PG Student, Department of ECE, Andhra University College of Engineering, Vishakapatnam-530003, A.P, India.

ABSTRACT

Skin Cancer Classification is a net application. Skin most cancers is a very large fitness problem in today's quickly developing populace now not solely for historical age humans however for all age groups. Skin Cancer is the most frequent human malignancy, is principally identified visually, establishing with a preliminary medical screening and accompanied probably through dermoscopic analysis, a biopsy and histopathological examination. Classification of skin lesions automatically the fine-grained heterogeneity in the appearance of skin lesions makes using pictures a challenging task. Therefore, this web app is useful for determining whether or not a person has cancer and, if so, what kind of cancer they have. A deep learning model with seven convolution layers and three neural layers was used to classify dermoscopic images from the HAM10000 dataset, which has seven classes. The proposed model was determined to have a test data accuracy of 99.01 percent. Experts in the field of skincancer diagnosis can use this information to better understand how the proposed model can assist them intheirwork.

1. INTRODUCTION

Given the rising prevalence of skin cancer and the significance for early detection, it is crucial to develop an effective method to automatically classify skin cancer. As the largest organ of the human body (1), the skin shoulders theresponsibility of protecting other human systems, which increases its vulnerability to disease (2). Melanoma was the most common cancer in both men and women with approximately 300,000 newcases (3) diagnosed globally in 2018. In addition to melanoma, two other major skin cancerdiseases, basal cell carcinoma (BCC) and squamous cell carcinoma (SCC), also had a relatively high incidence, with over 1 million cases in 2018 (4). As (5) reported, more skincancers are diagnosed each year than all other cancers combined in the United States. Fortunately, if detected early, the chances of cure will be greatly improved. According to (4), melanoma has a 5-year survival rate of 99% when it does not metastasize. If it metastasizes to other organs in the body, its survival rate reduces to 20%. However, because early indications of skin cancer are not always visible, diagnostic results are often dependent on the dermatologist's expertise (6). For inexperienced practitioners, an automatic diagnosis system is an essential tool for more accurate diagnoses. Beyond that, diagnosing skin cancer with naked eyes is highly subjective and rarely generalizable (7). Therefore, it is necessary to develop an automatic classification method for skin cancer that is more accurate, less expensive, andquicker to diagnose (8). Besides, implementing such automated diagnostic systems can effectively minimize mortality from skin cancers, benefiting both patients and the healthcare systems (9).However, owing to the complexity and diversity of skin disease images, achieving automatic classification of skin cancer is challenging. First of all, different skin lesions have lots of interclass similarities, which could result in misdiagnosis (10). For example, there exist various mimics of BCC in histopathological images, such as SCC and other skin diseases (11). As a result, it is difficult for the diagnosis systems to effectively discriminate skin malignancies from their known imitators. Secondly, several skin lesions differ within their same class in terms of color, feature, structure, size, and location (12). For example, the appearance of BCC and its subcategories is almost different. This makes it difficult to classify different subcategories of the same category. Furthermore, the classification algorithms are highly sensitive to the types of camera devices used to capture

s

images. When the test images come from a different domain, their performance suffers (13).Although traditional machine learning approaches are capable of performing well in particular skin cancer classification tasks, these algorithms are ineffective for complicated diagnostic demands inclinical practice. Traditional machine learning methods for skin cancer diagnosis typically involve extracting features from skin-disease images and then classifying the extracted features (14). For example, ABCD Rule (15), Menzies Method (16), and 7-Point Checklist (17) are effective methods for extracting various features from skin disease images. The handcrafted features are then classified using several classification methods such as SVM (18), XGBoost (19), and decision tree (20). Due to the restricted number of selected features, machine learning algorithms can often only classify a subset of skin cancer diseases and cannot generalize to a broader range of disease types(21). Besides, given the wide variety of skin cancers, it is not effective to identify each form of cancer solely based on handcrafted features (22).

EXISTING SYSTEM

Various neural networks using deep learning- based models such as PNASNet-5-Large, InceptionResNetV2, SENet154, and InceptionV4 have been proposed in the literature using the International Skin Imaging Collaboration (ISIC- ISBI) 2018 test dataset. The PNASNet-5-Large model gave the best results with 76% accuracy [7]. Another study used a linear classifier to classify 10 different skin lesions [8]. Feature extraction of 10 different skin lesions using a generic dermophyte image library containing 1300 clinical images was performed using an Alex Net whose last fully connected layer was replaced with a convolutional layer, resulting in an accuracy of 81.8% [8]. In another study, the public dataset of ISIC-ISBI 2016 was classified with random forest and support vector machine classifiers. By using random forest classifier on ISIC-ISBI 2016, the classification accuracy of theproposed system was 93.89%

PROPOSED SYSTEM

The HAM10000 dataset, which consists of seven classes and includes dermoscopic images, was classified using a deep learning model with seven convolution layers and three neural layers. The proposed model's test data accuracy percentage was found to be 99.01 percent. Using this data, specialists in the field of skin cancer diagnosis can use the proposed model. Over fitting of models is reduced.

ADVANTAGES

1. Accuracy is improved and accuracy of our model is 78%.
2. Model building takes less time.

2. LITERATURE SURVEY

Milton Md. AshrafulAlam Automated SkinLesion Classification with Deep Neural Networks for the 2018 ISIC Skin Lesion Analysis for Melanoma Detection Challenge

In this study, we delve further into the topic of utilizing specialized, deep-learning-based methods for detecting malignant melanomas and other skin lesions. One form of skin cancer, melanoma, is extremely dangerous. Accurately diagnosing melanoma in its earliest stages is crucial to increasing the likelihood of a complete recovery.Dermoscopic images showing both benign and malignant forms of skin cancer can be processed bya computer vision system, simplifying the process ofdetecting skin cancer. We conducted experiments with many neural networks in this paper, including PNASNet-5-Large, InceptionResNetV2, SENet154, and InceptionV4. These networks are all based on current deep learning techniques. The dermoscopic images are enhanced and processed properly before being uploaded to the cloud. Using the 2018 assignment dataset from the International Skin Imaging

Collaboration (ISIC), we evaluated our methods. For the PNASNet-5-Large model, our device received a perfect 0.76 validation rating. Perhaps the proposed methods' performances could benefit from further improvement and optimization with a larger training dataset and carefully selected hyper-parameter.

SerbanRadu S.J., L.I. Ichim, et al. Skin cancer is a type of cancer that develops in the skin tissue and can cause injury to the surrounding tissue, disability, and even death (Bucharest, Romania: The XIth International Symposium on Advanced Topics in Electrical Engineering, March 28-30, 2019).

After cervical and breast cancer, skin cancer accounts for a third of all cancer diagnoses in Indonesia. Early detection and effective treatment of skin cancer can significantly lessen or even reverse its potentially deadly effects. Doctors spend more time trying to determine if a lesion is cancerous or benign because of its similarities in structure. In this study, a system was built to automatically distinguish between skin cancer and benign tumour lesions using a Convolutional Neural Network (CNN). The suggested model hasthree discrete hidden layers, each with an associated output channel size (16), (32), and (64). The suggested model employs a number of optimizers, including SGD, RMSprop, Adam, and Nadam, and has a learning rate of 0.001. Adam optimizer has top overall performance, with an accuracy rate of 66%, in dividing the skin lesions in the ISIC dataset into four classes: Dermatofibroma, nevus pigmentosus, squamousmobile phone carcinoma, and melanoma. The results obtained perform better than the present skin cancer classification scheme.

[3] E. Bengtsson and P. Malm, "Screening for cervical cancer using automated analysis of PAP-smears," Comput. Math. Methods Med., vol. 2014, ID 842037, Mar. 2014.

Cervical cancer is one of the most deadly and common forms of cancer among women if noaction is taken to prevent it, yet it is preventable through a simple screening test, the so-called PAP-smear. This is the most effective cancer prevention measure developed so far. But the visual examination of the smears is time consuming and expensive and there have been numerous attempts at automating the analysis ever since the test was introduced more than 60 years ago. The first commercial systems for automated analysis of the cell samples appeared around the turn of the millennium but they have had limited impact on the screening costs. In this paper we examine the key issues that need to be addressed when an automated analysis system is developed and discuss how these challenges have been met over the years. The lessons learned maybe useful in the efforts to create a cost-effective screening system that could make affordable screening for cervical cancer available for all women globally, thus preventing most of the quarter million annual unnecessary deaths still caused by this disease.

[4] N. C. F. Codella et al., "Deep learningensembles for melanoma recognition indermoscopy images" IBM Journal of Researchand Development, Vol.61, pp.5:1- 5:15, 2017. Melanoma is the deadliest form of skin cancer. While curable with early detection, only highlytrained specialists are capable of accurately recognizing the disease. As expertise is in limitedsupply, automated systems capable of identifyingdisease could save lives,

[5] reduce unnecessary biopsies, and reduce costs. Toward this goal, we propose a system that combines recent developments in deep learning with established machine learning approaches, creating ensembles of methods that are capable of segmenting skin lesions, as well as analyzing the detected area and surrounding tissuefor melanoma detection. The system is evaluatedusing the largest publicly available benchmark dataset of dermoscopic images, containing 900 training and 379 testing images. New state-of-the-art performance levels are demonstrated, leading to an improvement in the area under receiver operatingcharacteristic curve of 7.5% (0.843 vs. 0.783), in average precision of 4% (0.649 vs. 0.624), and in specificity measured at the clinically relevant 95%sensitivity operating point 2.9 times higher than theprevious state-of-the-art (36.8%

[6] specificitycompared to 12.5%). Compared to the average of 8expert dermatologists on a subset of 100 test images,the proposed system produces a higher accuracy(76% vs. 70.5%), and specificity (62% vs. 59%)evaluated at an

[7] equivalent sensitivity (82%). Introduction Skin cancer is the most common cancer in the United States, with over 5 million casesdiagnosed each year [1]. Melanoma, the deadliestform of skin cancer, is involved in approximately 100,000 new instances every year in the United States, and over 9,000 deaths [2]. The cost to the

U.S. healthcare system exceeds $8 billion [3]. Internationally, skin cancer also poses a major public health threat. In Australia, there are over 13,000 new instances of melanoma yearly, leading to over 1,200 deaths [4]. In Europe, melanoma causes over 20,000 deaths a year [5]. In order to combat the rising mortality of melanoma, early detection is critical. Currently, highly trained experts and professional equipment are necessary for accurate and early detection of melanoma. Dermoscopy is a specialized method of high- resolution imaging of the skin that reduces skin surface reflectance, allowing clinicians to visualize deeper underlying structures. Using this device, specially trained clinicians have demonstrated a diagnostic accuracy as high as 75- 84% [7]. However, recognition performance drops significantly when the clinicians are not adequately trained [8, 9]. While in the United States there are over 10,000 dermatologists, inother areas of the world the supply of expertise is limited. For example, in Australia, the number of registered dermatologists in 2004 was approximately 340 [10], and in New Zealand, there were 16 [11]. Restricted access to expert consultation leads to additional challenges in providing adequate levels of care to the populations that are at risk. In order to address the limited supply of experts, there has been effort in the research community to develop automated image analysis systems to detect disease from dermoscopy images. Such 1 This paper will appear, in final form, in the IBM Journal of Research and Development, vol. 61, no. 4/5, 2017, as part of a special issue on “Deep Learning.” Please cite the IBM Journal official paper version of record. For more information on the journal, see: http: // www . research .ibm. com /journal/. ©IBM. 2 technology could be used as a diagnostic tool by primary care physicians and staff for regular screening, or by clinicians who are otherwise not trained to interpret dermoscopy images. Review articles covering a spectrum of publications have been recently presented [7, 12- 15]. The variety of automated image analysis techniques discussed is broad, but mostly restricted within the space of classical computer vision approaches, typically using combinations of low-level visual feature representations (color, edge, and texture descriptors, quantification ofmelanin based on color, etc.), rule-based image processing or segmentation algorithms, and classical machine learning techniques, such as k-nearest neighbor (kNN) and support vector machines(SVM). Some publications have presented algorithms that include segmentation of the lesion [16-21]. A team from the Pedro Hispano Hospital of Portugal sought to evaluate the performance of several (e.g., SVM and kNN) machine learning classifiers based on color, edge, and texture descriptors [22,23]. Other teams employed ensemble learning approaches [24-26]. Interestingly, some earlier work employed neural network machine learning approaches [27-31]. However, these were built on top of hand-coded low-level features. More recent work has begun to examine the efficacy of thestate-of-the-art deep learning approaches to image recognition within the dermatology and dermoscopy application domain [32,33]. Representations learned from the natural photo domain were leveraged, in conjunction with unsupervised and hand-coded features, to achieve state-of-the-art performance in a data of over 2,000 dermoscopy images [32]. However, the work was limited to lesion images thathad been manually presegmented: images were already cropped around the lesion of interest. In 2016, the International Skin Imaging Collaboration (ISIC) organized an international effort to aggregate a dataset of dermoscopic images from multiple institutions for the purposes of developing and evaluating clinical and automated techniques for the diagnosis of melanoma [34]. A snapshot of the dataset that contained the most complete set of annotations was selected to host a melanoma recognition challenge at the 2016 International Symposium on Biomedical Imaging (ISBI 2016). The challenge was titled "Skin Lesion Analysis toward Melanoma Detection" [35]. In total, 38 individual participants contributed 79 submissionsacross 3 image analysis tasks, including 43 submissions toward disease classification. This was the first publicly organized large-scale standardized evaluation of algorithms for the detection of melanoma. Top performing techniques involved deep learning approaches, including Deep Residual Networks for classification [36], and fully convolutional networks for segmentation [37,38]. In this work, we combine hand-coded feature extractors, sparse-coding methods, and SVMs, with more recent machine learning techniques, including deep residual networks and fully convolutional neural networks, into ensembles focused toward the task of melanoma recognition andsegmentation in dermoscopy images. We have chosen to use the ISBI 2016 dataset for evaluation, which provides an immediate comparison to dozens of prior algorithms, and opportunity for future comparisons. New state-of-the-art performance levels are demonstrated across a variety of evaluation metrics, including an almost tripling of specificity measured at 95% sensitivity. These results emphasize thatcombining a multitude of machine learning approaches can yield higher performance than relying on any one method alone, especially in regards to recognition of melanoma in dermoscopic images.

[4] N. C. F. Codella et al., "Deep learningensembles for melanoma recognitionin dermoscopy images" IBM Journal of Research and Development, Vol.61, pp.5:1- 5:15, 2017. Melanoma is the deadliest form of skin cancer. While curable with early detection, only highly trained specialists are capable of accurately recognizing the disease. As expertise is in limited supply, automated systems capable of identifying disease could save lives, reduce unnecessarybiopsies, and reduce costs. Toward this goal, wepropose a system that combines recent developments in deep learning with established machine learning approaches, creating ensembles of methods that are capable of segmenting skinlesions, as well as analyzing the detected area and surrounding tissue for melanoma detection. The system is evaluated using the largest publicly available benchmark dataset of dermoscopic images, containing 900 training and 379 testing images. New state-of-the-art performance levels are demonstrated, leading to an improvement inthe area under receiver operating characteristic curve of 7.5% (0.843 vs. 0.783), in averageprecision of 4% (0.649 vs. 0.624), and inspecificity measured at the clinically relevant95% sensitivity operating point 2.9 times higherthan the previous state-of-the-art (36.8%specificity compared to 12.5%). Compared to theaverage of 8 expert dermatologists on a subset of100 test images, the proposed system produces ahigher accuracy (76% vs. 70.5%), and specificity(62% vs. 59%) evaluated at an equivalent sensitivity (82%). Introduction Skin cancer is the most common cancer in the United States, with over 5 million cases diagnosed each year [1]. Melanoma, the deadliest form of skin cancer, is involved in approximately 100,000 new instances every year in the United States, and over 9,000 deaths [2]. Thecost to the U.S. healthcare system exceeds $8 billion[3]. Internationally, skin cancer also poses a major public health threat. In Australia, there are over 13,000 new instances of melanoma yearly, leading to over 1,200 deaths [4]. In Europe, melanoma causes over 20,000 deaths a year [5]. In order to combat the rising mortality of melanoma, early detection is critical. Currently, highly trained experts and professional equipment are necessary for accurate and early detection of melanoma. Dermoscopy is a specialized method of high-resolution imaging of the skin that reduces skin surface reflectance, allowing clinicians to visualize deeper underlying structures. Using this device, specially trained clinicians have demonstrated a diagnostic accuracy as high as 75-84% [7]. However, recognition performance drops significantly when the clinicians are not adequately trained [8, 9]. While in the United States there are over 10,000 dermatologists, in other areas of theworld the supply of expertise is limited. Forexample, in Australia, the number of registered dermatologists in 2004 was approximately 340 [10], and in New Zealand, there were 16 [11]. Restricted access to expert consultation leads to additional challenges in providing adequate levels of care tothe populations that are at risk. In order to address the limited supply of experts, there has been effort inthe research community to develop automated imageanalysis systems to detect disease from dermoscopy images. Such 1 This paper will appear, in final form, in the IBM Journal of Research and Development, vol. 61, no. 4/5, 2017, as part of a special issue on "Deep Learning." Please cite the IBM Journal official paper version of record. For moreinformation on the journal, see: http://www.research.ibm.com/journal/. ©IBM. 2 technology could be used as a diagnostic tool by primary care physicians and staff for regular screening, or by clinicians who are otherwise not trained to interpret dermoscopy images. Review articles covering a spectrum of publications have been recently presented [7, 12-15]. The variety of automated image analysis techniques discussed is broad, but mostly restricted within the space of classical computer vision approaches, typically using combinations of low-level visual feature representations (color, edge, and texture descriptors, quantification of melanin based on color, etc.), rule-based image processing or segmentation algorithms, and classical machinelearning techniques, such as k-nearest neighbor (kNN) and support vector machines (SVM). Some publications have presented algorithms thatinclude segmentation of the lesion [16-21]. A team from the Pedro Hispano Hospital of Portugal sought to evaluate the performance of several (e.g., SVM and kNN) machine learning classifiers based on color, edge, and texture descriptors [22,23]. Other teams employed ensemble learning approaches [24-26].Interestingly, some earlier work employed neural network machine learning approaches [27-31]. However, these were built on top of hand-coded low-level features. More recent work has begunto examine the efficacy of the state-of-the-art deep learning approaches to image recognitionwithin the dermatology and dermoscopy application domain [32,33]. Representationslearned from the natural photo domain were leveraged, in conjunction with unsupervised and hand-coded features, to achieve state-of-the-art performance in a data of over 2,000 dermoscopy images [32]. However, the work was limited to lesion images that had been manually pre- segmented: images were already cropped around the lesion of interest. In 2016, the International Skin Imaging Collaboration (ISIC) organized an international effort to aggregate a dataset of dermoscopic images from multiple institutions forthe purposes of developing and evaluating clinical and automated techniques for the diagnosis of melanoma [34]. A snapshot of the dataset that contained the most complete set of annotations was selected to host a melanoma recognition challenge at the 2016 InternationalSymposium on Biomedical Imaging (ISBI 2016). The challenge was titled "Skin Lesion Analysis toward Melanoma Detection" [35]. In total, 38 individual participants contributed 79 submissions across 3 image analysis tasks, including 43 submissions toward disease classification. This was the first publicly organized large-scale standardized evaluation of algorithms for the detection of melanoma. Top performing techniques involved deep learning approaches, including Deep Residual Networks for classification [36], and fully convolutional networks for segmentation [37,38]. In this work, we combine hand-coded feature extractors, sparse-coding methods, and SVMs, with more recent machine learning techniques, including deep residual networks and fully convolutional neural networks, into ensembles focused toward the task of melanoma recognition and segmentation in dermoscopic images. We have chosen to use theISBI 2016 dataset for evaluation, which provides an immediate comparison to dozens of prior algorithms, and opportunity for future comparisons. New state- of-the-art performance levels are

s

demonstrated across a variety of evaluation metrics, including an almost tripling of specificity measured at 95% sensitivity. These results emphasize that combininga multitude of machine learning approaches can yield higher performance than relying on any one method alone, especially in regards to recognition ofmelanoma in dermoscopic images.

3. CNN ALGORITHM

Deep Learning is turning into a very famous subset of laptop studying due to its excessive degree of overall performance throughout many sorts of data. A amazing way to use deep gaining knowledge of to classify pix is to construct a Convolutional Neural Network (CNN). The Keras library in Python makes it extraordinarily easy to construct a CNN. Computers see pictures the usage of pixels. Pixels in pix are typically related. For example, a sure team of pixels may additionally signify an part in an photograph or some different pattern. Convolutions use this to assist become aware of images. A Convolution multiplies a matrix of pixels with a filter matrix or kernel and sums up the multiplication values. Then the convolution slides over to the subsequent pixel and repeats the identical technique till all the photograph pixels have been covered.

As with regular Neural Networks, Convolutional Neural Networks are built from neurons with trainable weights and biases. To process its inputs, each neuron first does a dot product and then, if desired, adds a non-linearity to its output.

Common Neural Networks struggle when presented with complete visuals. Given a 32 by 32 by 3-inch image with three colour channels, a single fully connected neuron in the first hidden layer of a typical Neural Network would require 32 times 32 times 3 weights, or 3072 weights in total. This seems like a manageable amount, however this fully connected design doesn't work for very huge photos. For instance, a picture with dimensions of 200 by 200 by 3 would result in neurons with 200 by 200 by 3 weights, or 120,000 in total. Also, we'd all like to have plenty of these neurons, so the numbers would soon accumulate! Over fitting would occur quickly due to the large number of parameters, therefore it's clear that this kind of full connection is unnecessary.

By using the fact that the input is a series of images, Convolutional Neural Networks are able to limit the network's architecture for optimal performance. In particular, a ConvNet differs from a traditional Neural Network in that its neurons are laid out across the layers in three dimensions rather than just two. For instance, given an input image of size X, Y, and Z, each layer's neurons would only be connected to a small region of the layer before it rather than all of the neurons in a fully-connected manner. This would result in an output layer of size (1, 1), 1 (C), as the final stage of the ConvNet architecture would compress the entire image into a single vector of category scores, organised along thedepth dimension..

s

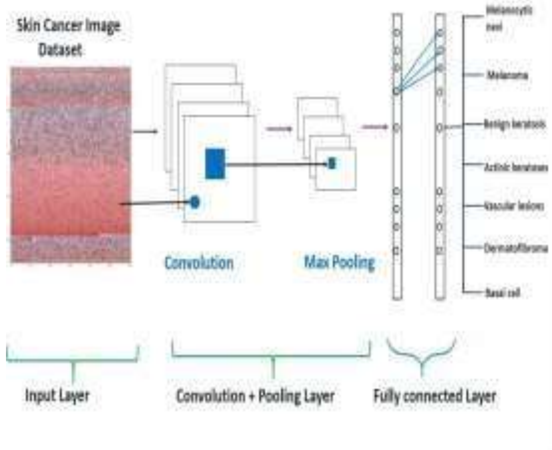

Fig 1: Convolutional-layerrepresentation

4. DATASET:

This HAM10000 ("Human against Machine with 10000 training images") dataset. It consists of dermatoscopic images (Kaggle) and renamed into ‘SKIN CARE’ which are used to train our model According to the different classifications. The ratio of the trainanedtestsetis80:20.

Fig 1:Diseases Images

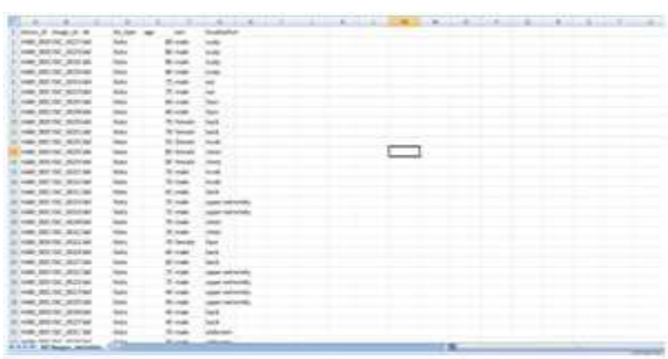

Fig 2: Dataset Values

s

5. OUTPUT SCREENS:

Fig 3:Signup page

Fig 6:In the above screen we got result based on input image

Fig 4:Login Page

Fig 5:In the above screenshots we are uploading image for skin cancer detection

S

6. CONCLUSION

We here by conclude that Skin Cancer Classificationusing CNN is implemented in three modules; the first module is about performing image preprocessing. All the images are resized into a dimension of 100 x 75 in order to train, test, and predict the classes and to calculate the accuracy of the model efficiently. In the second module, Convolution Neural Network is applied to train the model and test it. To provide better accuracy and to avoid computational complexity the model is built using the Convolutional Neural Network algorithm with good accuracy.

REFERENCES

[1] American Cancer Society: Cancer facts andfigures 2018. Available: https://www.cancer.org/content/dam/cancer- org/research/cancer-factsand-statistics/annual- cancer-facts-and-figures/2018/cancer-facts- andfigures-2018.pdf , Accessed: 15 Aug 2018.

[2] N. C. F. Codella et al., "Deep learning ensembles for melanoma recognition in dermoscopy images" IBM Journal of Research and Development, Vol.61, pp.5:1- 5:15, 2017.

[3] N. Codella et al., "Deep learning, sparse coding, and SVM for melanoma recognition in dermoscopy images", LNCS, Springer, vol. 9352, pp. 118–126, 2015. Available: https://doi.org/10.1007/978-3- 319-24888-2_15 , Accessed: 15 Aug 2018

[4] N. K. Mishra and M. E. Celebi."An overview of melanoma detection in dermoscopy images using image processing and machine learning", 2016. Available: https://arxiv.org/abs/1601.07843 , Accessed: 15 Aug 2018.

[5] Masood, A. & Al-Jumaily, A. A. Computer aideddiagnostic support system for skin cancer: a review of techniques and algorithms. Int. J. Biomed.Imaging 2013, vol. 323268, 2013.

[6] Gutman, D. et al. Skin lesion analysis toward melanoma detection. International Symposium on Biomedical Imaging (ISBI), (International SkinImaging Collaboration (ISIC), 2016.

[7] Binder, M. et al. Epiluminescence microscopy-based classification of pigmented skin lesions using computerized image analysis and an artificial neural network. Melanoma Res., Vol. 8, pp. 261–266, 1998.

[8] Burroni, M. et al. Melanoma computer-aided diagnosis: reliability and feasibility study. Clin. Cancer Res., Vol. 10, pp. 1881–1886, 2004.

[9] Schindewolf, T. et al. Classification ofmelanocytic lesions with color and texture analysis using digital image processing. Anal. Quant. Cytol. Histol., Vol. 15, pp. 1–11, 1993.

[10] Mnih, V. et al. Human-level control through deep reinforcement learning. Nature, vol. 518, pp. 529–533, 2015.

[11] Silver, D. et al. Mastering the game of Go with deep neural networks and tree search. Nature, vol. 529, pp. 484–489, 2016.

[12] Russakovsky, O. et al. Imagenet large scale visual recognition challenge. Int. J. Comput. Vis.,vol. 115, pp. 211–252, 2015.

[13] I. A. Ozkan, and M. Koklu, "Skin Lesion Classification using Machine Learning Algorithms", Intelligent Systems and Applications in Engineering, vol. 5, no. 4, pp.285-289, 2017.

[14] L. Bi, J. Kim, E. Ahn, D. Feng, and M.Fulham, "Automatic melanoma detection viamulti-scale lesion-biased representation and joint reverse classification", 2016 IEEE 13th Int. Symposium on Biomedical Imaging (ISBI), pp. 1055-1058, 2016.

[15] R. Chakravorty, S. Liang, M. Abedini and R.Garnavi, "Dermatologistlike feature extraction from skin lesion for improved asymmetry classification in PH2 database", 38th Int. Conf. of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 3855-3858, 2016.

[16] Z. Waheed, A. Waheed, M. Zafar, and F. Riaz, "An Efficient Machine Learning Approach for the Detection of Melanoma using

Dermoscopic Images", Int. Conf. on Communication, Computing and Digital Systems (C-CODE), IEEE, pp. 316-319, 2017.

[17] Premaladha, J., and K. S. Ravichandran. "Novel approaches for diagnosing melanoma skin lesionsthrough supervised and deep learning algorithms."
Journal of medical systems 40.4 (2016): 96

[18] Y. LeCun, Y. Bengio, G.Hinton, "Deep learning", Nature, vol. 521, PP.436–444, 2015.

[19] Convolutional Neural Networks (CNNs / ConvNets), the Stanford CS class notes, Spring 2017 Assignments, Available:
http://cs231n.github.io/convolutional-networks/,Accessed: 15 Aug 2018

s