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SKIN LESION ANALYSIS TOWARDS MELANOMA DETECTION USING IMAGE PROCESSING: SURVEY & RESEARCH PAPER

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ABSTRACT

Skin cancer is one of the most dangerous diseases in the world. Correctly classifying skin lesions at an early stage could aid clinical decision-making by providing an accurate disease diagnosis, potentially increasing the chances of a cure before cancer spreads. However, achieving automatic skin cancer classification is difficult because the majority of skin disease images used for training are imbalanced and in short supply; meanwhile, the model's cross-domain adaptability and robustness are also critical challenges. Recently, many deep learning-based methods have been widely used in skin cancer classification to solve the above issues and achieve satisfactory results. Nonetheless, reviews that include the abovementioned frontier problems in skin cancer classification are still scarce. Therefore, in this article, we provide a comprehensive overview of the latest deep learning-based algorithms for skin cancer classification. We begin with an overview of three types of dermatological images, followed by a list of publicly available datasets relating to skin cancers. After that, we review the successful applications of typical convolutional neural networks for skin cancer classification. As a highlight of this paper, we next summarize several frontier problems, including data imbalance, data limitation, domain adaptation, model robustness, and model efficiency, followed by corresponding solutions in the skin cancer classification task. Finally, by summarizing different deep learning-based methods to solve the frontier challenges in skin cancer classification, we can conclude that the general development direction of these approaches is structured, lightweight, and multimodal. Besides, for readers' convenience, we have summarized our findings in figures and tables. Considering the growing popularity of deep learning, there are still many issues to overcome as well as chances to pursue in the future.

Deep learning is a new research area within modern technology using microservices with big data, virtual reality and also augmented reality. Due to the development of huge computing capacity, technologies such as deep learning application using MobileNet (CNN) has revolutionized image classification. Deep learning can be used to classify the different types of skin cancer types. This learning technique uses different algorithms such as MobileNet CNN algorithms. MobileNet algorithms are suitable ways to recognize the images from the input and give accurate results. In this current work, MobileNet CNN is used in our data set to classify skin disease types according to our input.

Keywords: Dermoscopy Image, Melanoma Recognition, Residual Network, Fisher Vector, Deep Learning.

I. INTRODUCTION

According to the WHO's statistics, the number of people will affected by the skin cancer will rise up to almost 13.1 millions by 2030. Skin cancer is a condition in which there is an abnormal growth of melanocytic cells in the skin. Malignant melanoma class of skin cancer is generally caused from the pigment-containing cells known as melanocytes. Melanoma is found among non-Hispanic white males and females, and results in approximately 75% of deaths associated with skin cancer [1]. According to the world cancer report, the primitive reason of melanoma is ultra-violate light exposure in those people who have low level of skin pigment. The UV ray can be from the sun or any other sources and approximately 25% of malignant can be from moles [2]. Considering the limited availability of the resources, early detection of skin cancer is highly important. Accurate diagnosis and feasibility of detection are vital in general for skin cancer prevention policy. Skin cancer detection in early phases is a challenge for even the dermatologist. In recent times, we have witnessed extensive use of deep learning in both supervised and unsupervised learning problems. One of these models is Convolution Neural Networks (CNN) which has outperformed all others for object recognition and object classification tasks. CNNs eliminate the obligation of manually handcrafting features by learning highly discriminative features while being trained end-to-end in a supervised manner.

Convolutional Neural Networks have recently been used for the identification of skin cancer lesions. Several CNN models have successfully outperformed trained human professionals in classifying skin cancers. Several methods like transfer learning using large datasets have further improved the accuracy of these models. VGG-16 is a convolutional neural system that is prepared on more than a million pictures from the ImageNet database. The system is 16 layers profound and can arrange pictures into 1000 item classifications, for example, console, mouse, pencil, and numerous creatures. Accordingly, the system has learned rich component portrayals for a wide scope of pictures. The system has a picture info size of 224-by-224. The model accomplishes 92.7% top-5 test precision in ImageNet, which is a dataset of more than 14 million pictures having a place with 1000 classes.

II. LITERATURE SURVEY

Diagnosis of an unknown skin lesion is crucial to enable proper treatments. Early detection of melanoma in dermoscopic images significantly increases the survival rate. Only highly trained dermatologists are capable of accurately recognising melanoma skin lesions. However, the accurate recognition of melanoma is extremely challenging due to the following reasons: low contrast between lesions and skin, visual similarity between melanoma and non-melanoma lesions, etc. As expertise is in limited supply, reliable automatic detection of skin tumours i.e., systems that can automatically classify skin lesions will be very useful to increase the accuracy and efficiency of pathologists. Here we present some of the early studies and systems for the detection of skin melanoma.

1) Skin Lesion Analysis Towards Melanoma Detection Using Deep Learning Network

In this study, the author worked on two deep learning methods named the Lesion Indexing Network (LIN) and the Lesion Feature Network (LFN), to address three main tasks emerging in the area of skin lesion image processing.

- Lesion Segmentation
- Lesion Dermoscopic Feature Extraction
- Lesion Classification

The author proposed a deep learning framework consisting of two fully convolutional residual networks (FCRN), simultaneously producing the segmentation result and the coarse classification result. A lesion index calculation unit (LICU) is developed to refine the coarse classification results by calculating the distance heat map. A straightforward CNN is proposed for the dermoscopic feature extraction task. The author used ISIC 2017 dataset to evaluate the proposed deep learning framework.

Based on an experiment conducted by the author, the proposed (LIN) for lesion segmentation and classification outperforms the existing deep learning frameworks whereas the proposed LFN achieves the best average precision and sensitivity, for dermoscopic feature extraction, which demonstrates its excellent capacity for addressing the challenge.

2) Automatic Skin Lesion Segmentation Using Deep Fully Convolutional Networks with Jaccard Distance.

In this paper, the author presented a fully automatic method for skin lesion segmentation by optimal utilization of a trained 19-layer deep convolutional neural network (CNN) that does not rely on prior knowledge of the data. The author implemented a set of strategies to ensure effective and efficient learning with limited training data. A novel loss function based on Jaccard distance to eliminate the need for sample re-weighting is also developed, due to the strong imbalance between the number of foregrounds and background pixels as a typical procedure when using cross entropy as the loss function for image segmentation. The author used two publicly available databases which are ISBI 2016 and PH2 database to evaluate the effectiveness, efficiency, as well as generalization capability of the proposed framework. Experiments conducted by the author concluded that the proposed method outperformed other state-of-the-art algorithms on these two databases.

3) Dermatologist-Level Classification of Skin Cancer with Deep Neural Networks.

In this paper, the author demonstrates the classification of skin lesions using a single CNN, trained end-to-end from images directly, using only pixels and disease labels as inputs. Here firstly author trained CNN using a dataset of 129,450 clinical images—two orders of magnitude larger than previous datasets consisting of 2,032 different diseases.

The first case represents the identification of the most common cancers, the second represents the identification of the deadliest skin cancer.

The experiment conducted by the author shows that CNN achieves better performance on all tested experts across both tasks, demonstrating an artificial intelligence capable of classifying skin cancer with a level of competence comparable to dermatologists.

4) Automated Melanoma Recognition in Dermoscopy Images via Very Deep Residual Networks.

In this research, the author proposes a new method for melanoma recognition by using deep convolutional neural networks (CNNs) and comparing it with existing methods which implies either low-level hand-crafted features or CNNs with shallower architectures. The author concluded that their system, substantially deeper networks can acquire richer and more discriminative features for more accurate recognition. To take full advantage of very deep networks, the author proposed a set of schemes to ensure effective training and learning under limited training data. The method applies the following steps:Apply the residual learning to cope with the degradation and overfitting problems when a network goes deeper. It will ensure the performance gains achieved by increasing network depth.

Construct a fully convolutional residual network (FCRN) for accurate skin lesion segmentation, and further enhance its capability by incorporating a multi-scale contextual information integration scheme. Finally, integrate the proposed FCRN (for segmentation) and deep residual networks (for classification) to form a two-stage framework. This framework enables the classification network to extract more representative and specific features based on segmented results instead of the whole dermoscopy images, further reducing the insufficiency of training data. For evaluation purpose author used ISBI 2016 Skin Lesion Analysis Towards Melanoma Detection Challenge dataset.

5) Skin Lesion Analysis System for Melanoma Detection with an Effective Hair Segmentation Method.

Here, proposes a non-invasive automated skin lesion analysis system for the early detection of melanoma using image processing techniques and mobile technologies. Hair detection and removal are performed for effective classification and extraction of features of the skin wound. A fast marching in painting algorithm is used for hair removal. The efficiency of the system is improved by removing the hair that may exist on the skin. The experimental result is evaluated on the PH2 database from Pedro Hispano hospital.

6) Learning Deep Representations of Medical Images using Siamese CNNs with Application to Content-Based Image Retrieval.

In this study, the author proposes a deep Siamese CNN (SCNN) architecture that can be trained with only binary image pair information to learn image representations with less supervision involved. The main motive behind this is that most of the studies limit their approach to a single supervised convolutional neural network (CNN). Author evaluates the learned image representations on a task of content-based medical image retrieval using a publicly available multiclass diabetic retinopathy fundus image dataset. The results of the experiment show that the author's system i.e., deep SCNN is comparable to the state-of-the-art single-supervised CNN, and requires much less supervision for training.

7) Skin Lesion Segmentation and Classification for ISIC 2018 Using Traditional Classifiers with Hand-Crafted Features.

This study gives the required description of the methods used to obtain submitted results for Task 1 and Task 3 of ISIC 2018: Skin Lesion Analysis Towards Melanoma Detection. The approach used in this study is to use traditional classifier methods with hand-crafted features.

The approach begins with the design of a colour classifier to distinguish lesion tissue from normal skin tissue based exclusively on RGB colour vectors. Gaussian mixture models (GMMs) are used to model the probability density functions of the tissue types. A Bayesian classifier framework is used to estimate the posterior probability of being a lesion pixel for all pixels in a given image. A support Vector Machine (SVM) is used for the adaptive selection of the segmentation threshold for each image.

The classification method for lesion diagnosis in this study is accomplished by using an SVM classifier with 200

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hand-crafted features. The features are computed from the RGB image along with the lesion segmentation mask obtained.

8) Automated Skin Lesion Analysis Based on Colour and Shape Geometry Feature Set for Melanoma Early Detection and Prevention.

Here in this study, the author introduces an automated skin lesion segmentation and analysis for early detection and prevention based on colour and shape geometry. The system further incorporates other feature sets such as colour to determine the lesion type. The author used the PH2 Dermoscopic image database from Pedro Hispano Hospital for evaluation and testing purposes. The systems approach of analysing the shape geometry and the colour will be helpful to detect atypical lesions before it grows and becomes melanoma case.

III. OBJECTIVES

- Comprehensive two-stage approach based on very deep CNNs with a set of effective training schemes to ensure the performance gains of increasing network depth.
- Use of limited training data for automated melanoma recognition.
- Use of very convolution neural network for accurate skin lesion segmentation.
- Fast and accurate melanoma detection (Melanoma or Not) in early stages of skin cancer.

IV. METHODOLOGY

An early and fast detection of melanoma skin cancer which can saves the patients life. The framework consist of deep learning method and segmentation is proposed which detect melanoma in early stages of cancer and achieved improve results in terms of both accuracy and time.

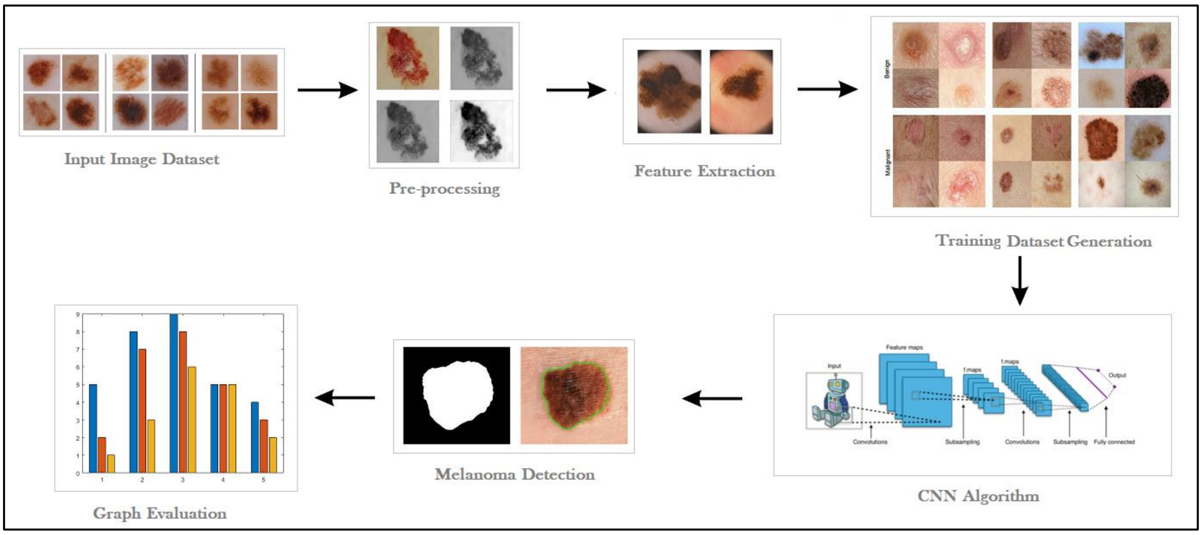

Figure 1: System Architecture

Following are the steps involved in system architecture:

- Input image dataset to the system.
- Pre-processing is performed to enhance image quality and resize the image.
- Several features are extracted from input image dataset from which training file is generated.
- Generated training file dataset and new test input images are pass to CNN classification algorithm.
- The output of CNN algorithm is melanoma detection i.e the input test show melanoma or not. At the end graphical evaluation is perform to check the performance of proposed system.

Data Flow Diagram

A data flow diagram (DFD) is a nothing but a graphical representation of the “flow” of data through an information system, which is used for modelling its Process aspects. Mostly DFD’s are very preliminary step which is used for representing overview of system which can later explain in detail. DFDs can also be used for the visualization of data processing (structured design). A DFD shows what kind of information will be input to and output from the system, where the data will come from and go to, and where the data will be stored. It does not show information about the timing of processes, or information about whether processes will operate in

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sequence or in parallel.

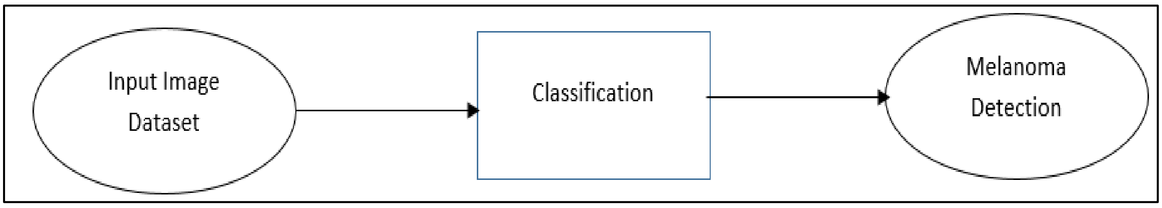

Figure 2: DFD Level-0

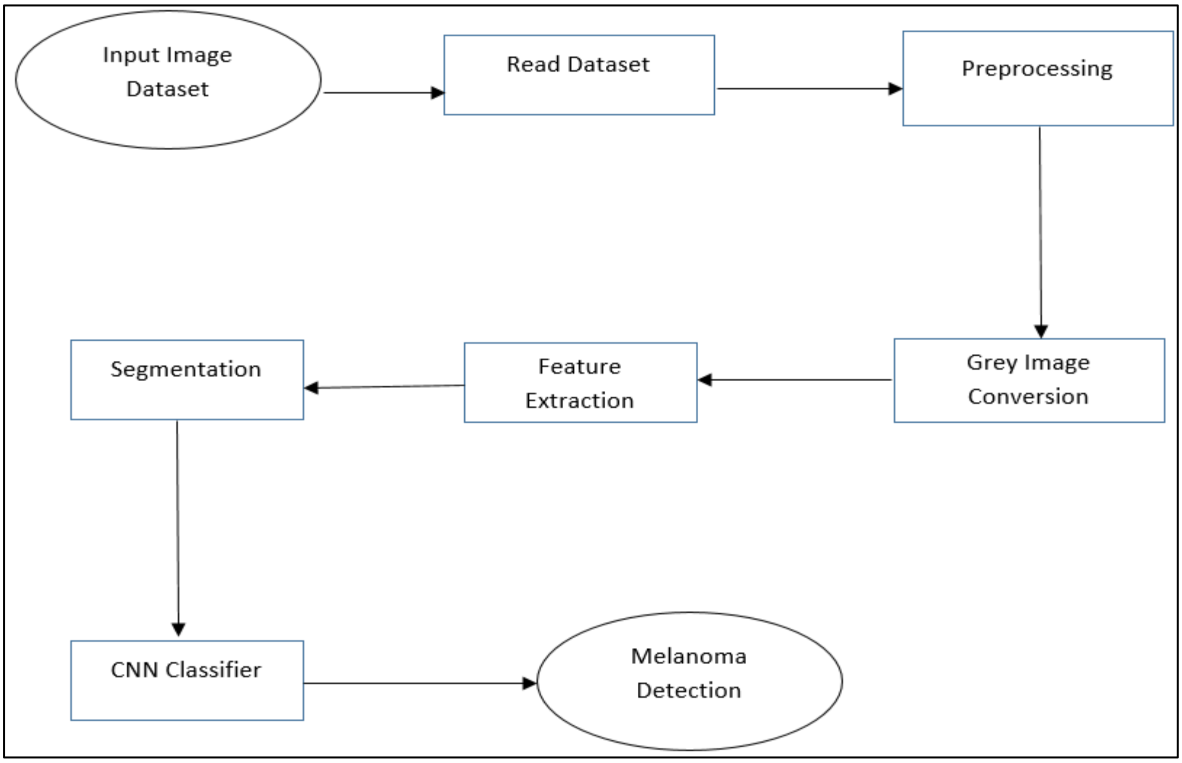

Figure 3: DFD Level-2

V. MODELING AND ANALYSIS

1. Input Data Set and Pre-Processing

2. Feature Extraction

i. Feature extraction using HU Moments:

ii. Feature extraction using Haralick:

iii. Feature extraction using Histogram:

iv. GLCM (Gray Level Co-occurrence Matrix):

3. Machine Learning Classification

i. SVM

ii. Navie Bayes

iii. Precision

4. Deep Learining Classification

i. CNN

1. Input Data Set and Pre-Processing

As a first step, create a directory of the images from different sources. In the current dataset, we have 10015 images which have a size of 500x 500 pixels of RGB images. The dataset is ISIC which is used to download the image it is a public dataset which provides free data set for python simulation.

2. Feature Extraction

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i. Feature extraction using HU Moments:

Hu Moments are normally extracted from the silhouette or outline of an object in an image. By describing the silhouette or outline of an object, we are able to extract a shape feature vector (i.e. a list of numbers) to represent the shape of the object.

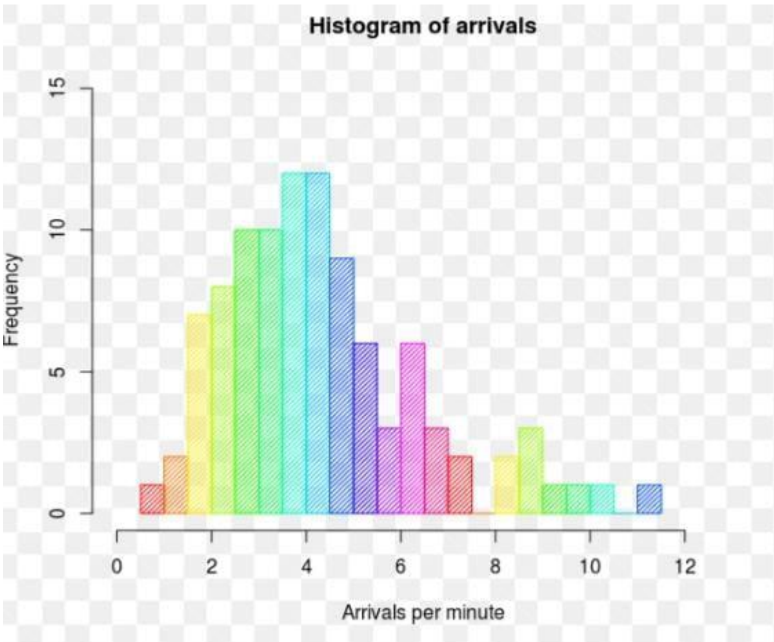
We can then compare two feature vectors using a similarity metric or distance function to determine how "similar" the shapes are.

ii. Feature extraction using Haralick:

Haralick texture features are calculated from a Gray Level Co-occurrence Matrix, (GLCM), a matrix that counts the co-occurrence of neighboring gray levels in the image. The GLCM is a square matrix that has the dimension of the number of gray levels N in the region of interest (ROI).

iii. Feature extraction using Histogram:

A histogram is used to summarize discrete or continuous data. In other words, it provides a visual interpretation of numerical data by showing the number of data points that fall within a specified range of values (called "bins"). It is similar to a vertical bar graph. However, a histogram, unlike a vertical bar graph, shows no gaps between the bars.



iv. GLCM (Gray Level Co-occurrence Matrix):

A histogram is used to summarize discrete or continuous data. In other words, it provides a visual interpretation of numerical data by showing the number of data points that fall within a specified range of values (called "bins"). It is similar to a vertical bar graph. However, a histogram, unlike a vertical bar graph, shows no gaps between the bars.

3. Machine Learning Classification

i. SVM (Support Vector Machine)

SVM (Support Vector Machine) is a supervised machine learning algorithm which is mainly used to classify data into different classes. It uses a technique called the kernel trick to transform our data and then based on these transformations it finds an optimal boundary between the possible outputs.

ii. Navie Bayes :

Naïve Bayes algorithm is a supervised learning algorithm, which is based on Bayes theorem and used for solving classification problems. It is mainly used in text classification that includes a high-dimensional training dataset. It is a probabilistic classifier, which means it predicts on the basis of the probability of an object.

iii. Precision :

Precision is one indicator of a machine learning model's performance – the quality of a positive prediction made by the model. Precision refers to the number of true positives divided by the total number of positive predictions (i.e., the number of true positives plus the number of false positives).

4. Deep Learining Classification

CNN (Convolution in Neural Network) :

A CNN is a kind of network architecture for deep learning algorithms and is specifically used for image recognition and tasks that involve the processing of pixel data. There are other types of neural networks in deep learning, but for identifying and recognizing objects, CNNs are the network architecture of choice.

VI. CONCLUSION

All over the world, skin cancer is considered one of the deadliest types of cancer. Here, we construct a computer aided skin lesion classifier system using different deep neural network architectures with feature extraction segmentation. We also used CNN classifier for melanoma and non-melanoma images detection. And we used several data pre-processing and augmentation rules applied to lessen the effect of class imbalance characteristic of Input Image Dataset. Results shows that our system provides better accuracy compare to existing system.

The model resulted in an 81% accuracy using the dice coefficient on the training set. The dice coefficient is much lower on the training set however the confusion matrix outputs a high true and false positive rate on a set that contains positive and negative samples. This indicates that the model is great at distinguishing between images with no cancer nodules compared to the ones with cancer. I believe with more hyperparameter tuning and model training the accuracy could be increased.

VII. FUTURE WORK

AI has a wide scope in healthcare settings, for both diagnosis and therapeutic purposes. One of the major challenges for AI is the need for training the machine learning approach with the continuous feeding of data. Clinicians and patients should be aggregable to continuously provide images for better results with AI applications. Anonymity and privacy should be taken seriously when feeding the data into AI systems. Harmonization of the regulatory norms across the globe will be the key to the widespread use of AI systems in healthcare.

Larger studies among dermatologists are needed to provide more insights about their perceptions and acceptance of ML in the diagnosis of skin cancers.

Many images are irrelevant and poor. With more accurate good image quality we could make a more accurate result prediction, a more efficient deep learning model would be capable of alleviating these additional challenges and implementation of the same in GUI as web-based or android based on windows application platforms. Also, with a greater number of images included in the dataset, we can achieve even much higher accuracy.

VIII. REFERENCES

[1] Spencer Shawna Bram Hannah J, Frauendorfer Megan and Hartos Jessica L. 2017. Does the Prevalence of Skin Cancer Differ by Metropolitan Status for Males and Females in the United States? Journal of Preventive Medicine 3, 3:9 (2017), 1–6. https://doi.org/10.21767/2572-5483.100019

[2] Wild CP Stewart BW. 2014. World Cancer Report. Retrieved March 16, 2019 from: http://publications.iarc.fr/Non-Series-Publications/World-Cancer-Reports/World-Cancer-Report-2014

[3] Yuexiang Li, Linlin Shen,"Skin Lesion Analysis towards Melanoma Detection Using Deep Learning Network", Sensors 2018,18,556, p-1-16.

[4] Yading Yuan, Ming Chao, Yeh-Chi Lo, "Automatic Skin Lesion Segmentation Using Deep Fully Convolutional Networks with Jaccard Distance", IEEE Transactions on Medical Imaging, Volume: 36, Issue: 9, Sept. 2017.

[5] Andre Esteva, Brett Kuprel, Roberto A. Novoa, Justin Ko, Susan M. Swetter, Helen M. Blau, and Sebastian Thrun,"Dermatologist-level classification of skin cancer with deep neural networks", Vol 542, p-115-127, Springer Nature Feb-2017.

[6] 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, Volume: 36, Issue: 4, April 2017.

[7] Supriya Joseph, Janu R Panicker,"Skin Lesion Analysis System for Melanoma Detection with an Effective Hair Segmentation Method", IEEE International Conference on Information Science (ICIS), IEEE Aug-2016.

[8] Yu-An Chung, Wei-Hung Weng, "Learning Deep Representations of Medical Images using Siamese CNNs with Application to Content-Based Image Retrieval",31st Conference on Neural Information Processing Systems (NIPS 2017).

[9] Russell C. Hardie, Redha Ali, Manawaduge Supun De Silva, and Temesguen Messay Kebede,"Skin Lesion Segmentation and Classification for ISIC 2018 Using Traditional Classifiers with Hand-Crafted Features", Corenell University Library, Image and Video Processing, July 2018.