IJCSN - International Journal of Computer Science and Network, Volume 8, Issue 3, June 2019
ISSN (Online) : 2277-5420
www.IJCSN.org
Impact Factor: 1.5

Segmentation of Skin Lesion towards Melanoma Skin Cancer Classification

[1] Nay Chi Lynn; [2] Nu War

[1] Image Processing Lab, University of Computer Studies, Mandalay
Mandalay, Myanmar

[2] Faculty of Computer Systems and Technologies, University of Computer Studies, Mandalay
Mandalay, Myanmar

Abstract - Melanoma is one form of skin cancer which is one of the most hazardous types of cancer happened in people. Incidence of skin cancer has been increasing over decades due to excess exposure of radiations from sun causing erosion to skin melanin. The automatic detection of melanoma in dermatological images is a challenging task because of the diverse contrast of skin lesions, the magnitude of melanoma within the class, and the utmost optical similarity to melanoma and lesions other than melanoma and the beingness of many artifacts in the lesion pictures. In this work, the skin lesion analysis system to aid for the melanoma detection is proposed. Firstly, the skin lesion from dermoscopy images is automatically segmented with the use of texture filters. Then, the features according to the underlying ABCD dermatology rules are then extracted from the segmented skin lesion. Finally, the system is classified by random subspace ensemble classifier in order to determine the images as benign or malignant melanoma
The performance of the study was experimented with their precision and it achieves with compromising results.

Keywords - *Melanoma; Skin Cancer; Segmentation; Feature Extraction; Classification*.

1. Introduction

Skin cancer is one of the most usual cancers in Caucasian. It is also one of the quickest spreading cancers of the world and the occurrence has increased in the previous 30 years. Due to an accurate patient awareness, delay or lack of diagnosis by the family doctor, accessible and accurate information is required as a trend for the pre-selection of general awareness solutions.

The skin is the most important part of the body and has various infectious diseases, sunshine and many other problems and also facilitates to keep body temperature [1]. Skin cancer can be found in various types such as melanoma, basal cell carcinoma and squamous cell carcinoma and melanoma is nearly indeterminable [2]. The perception of a melanoma at a primary stage can be influenced to cure this disease. This cancerous proliferation is characterized by the onset of DNA damage to unrepaired skin cells (caused in most cases by sunlight, ultraviolet light, or sunbeds) that cause skin cell mutations (genetic defects) to multiply speedily and form malignant tumors.

In the health of the skin, diagnosis or diagnostics is the process of identifying the texture or problem of the skin, depending on their signs, symptoms and the results of various diagnostic procedures. The conclusion obtained through this process is called diagnosis. The diagnosis system is a system that can be used to analyze problems by answering a few questions that will lead to a solution to the problem. Skin cancer is a malignant tumor that grows in skin cells and is trustable for more than 50% of every cancers. Luckily, skin cancer in child is rare to occur. When a melanoma develops, it is mostly pigmented nevus (moles) (greater than 6 mm in diameter), asymmetric, with irregular edges and staining. Bleeding, itching and mass under the skin are other signs of cancer. When children receive cancer radiation therapy, violence in the irradiated area has a high risk of cancer. The skin cancer detection system screens symptoms of skin cancer and diagnoses melanoma at an early stage so that users can prevent their health as quickly as possible. The system for detecting skin cancer saves the physician a lot of time and helps to make a more accurate diagnosis. It is also possible to easily evaluate the future development of the skin by dialysis of the current age of the skin and to present to the customer the best skin cancer stage.

Fig. 1: Workflow Diagram of Automatic Classification of Skin Lesion

In 1985, the group at New York University recognized the need to educate doctors and the general public, about melanoma in the first clinical presentation, and the acronym ABCD (asymmetry, edge irregularity, color variety, diameter> 6 mm) [4]. For the detection of skin lesions caused by melanoma, ABCD features are most commonly used to extract features based on a morphological analysis of dermal images of skin lesions.

Once the appropriate properties have been determined, the next step is to distinguish malicious structures from corresponding ones. At this phase, the region of interest in the image of the lesion is designated to a class of cancer, good or healthy.

As part of the diagnosis, malignant tissue layers can also be classified.

2. Dataset Description

The datasets used in this work are ISBI dataset and PH2 dataset. There are 900 training images associated with its groundtruth images and 379 testing images in ISBI 2016 dataset and 200 images are totally included in PH2 dataset. The images in both datasets are dermoscopy images which means that images are acquired by standard camera vs dermoscopy.

The ISBI dataset is publicly accessible as a challenging dataset in which International Skin Imaging Challenging (ISIC)'s collecting efforts for matching the picture of the skin lesion. This challenge is leveraged as a database of dermoscopic skin images where the images are internationally collected from authoritative clinical hospitals, acquired from several equipment used at each clinical hospital. The available images are tested for both concealment and quality assurance. Overall ISBI skin lesion images are categorized into two classes. Nearly 30.30 % of the images were malignant (273 images in the training set).

The PH2 image dataset includes a series of 200 percutaneous images for diagnosing symptoms, and identification of multiple percutaneous structures carried out by a professional dermatologist. The PH2 database can also be used free of charge for research and benchmark purposes.

The dermoscopy images are challenging with variety of artifacts as shown is figure 2.

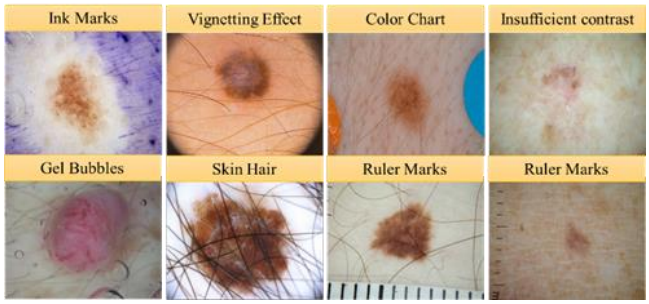

Fig. 2: Example Images in Dermoscopy Dataset

3. Methodology

The clinically oriented dermoscopy imaging systems based on machine learning algorithms comprise three principal steps: segmentation of lesion areas, feature extraction and classification of these features to assess whether the input lesion will be melanocyte or non-melanocyte skin lesions. The overall systematic scheme of the skin lesion classification system is depicted in the figure 3.

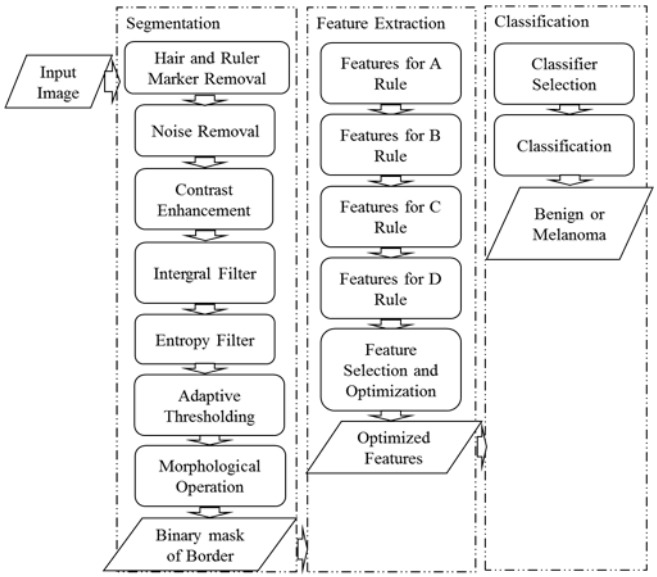

Fig. 3: The Architecture of Proposed Skin Lesion Classification System

3.1 Segmentation

There are different techniques in the technical literature for extracting lesion regions of interest from dermoscopic skin images. The segmentation of the lesion is a very fundamental portion in the analysis of the dermatologically inspected image, as it allows for the identification of different features specific to the lesion. The segmentation of a lesion means the separation of lesions (regions of

interest) from the surrounding normal skin area. There is prior pre-processing step ahead of segmentation process as some issues are included with the dataset:

1) Vignette present in some images
2) Hair present in various densities
3) Insufficient contrast between lesion and background skin
4) Various color charts, ink markers, ruler markers and gel bubbles in some images

For these reasons the raw images are pre-processed before segmenting the skin lesion.

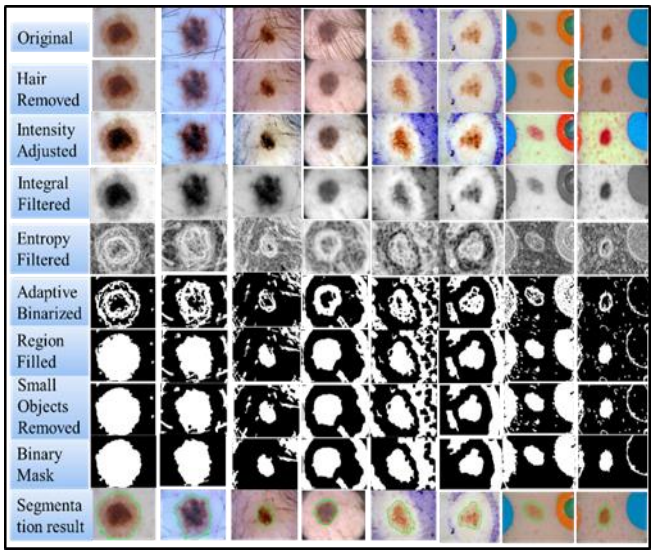

Fig. 4: The step by step segmentation results

The purpose of the hair removal in pre-processing step is to enhance the image by deposing of outcast artifacts. The manipulation of obstructive hair is an important pre-processing step for all computer applications associated with dermal images. Standard marks are treated similarly and imitate hair as a structure. Hair and Ruler Maker detection and removal is the one which replace hair pixels by neighboring pixels.

Image imperfections may degrade the performance, making the image enhancement procedure necessary. Image adjustment is used for intensity transformations of gray scale images by increasing intensity while leaving the contrast unchanged in the whole image. This also means that increasing intensity can be viewed as brightening the image. The shape and edges of image are enhanced to clarify the image, improve better performance and obtain high contrast. Besides, contrast adjustment can precise the picture boundary and get the better accuracy for segmentation.

In the segmentation process of this study, the use of texture filters and thresholding are applied. Integral image is an effective image representation from that local image sums can be calculated quickly and can be deployed in getting better texture rendering speed. The summed area table is computed in order to get the integral image. Given an integral image, the integral filter filters the image. The filter size does not affect the speed of the filtering operation.

Next, the local entropy of image in grayscale version is computed. The entropy magnitude of the 9-by-9 neighborhood amongst the nearby pixel contained in each output pixel in the image is then computed. The lighter pixels of the filtered region correlate with the neighborhood of the original image with higher entropy.
Then, the morphological operation is used to morphologically smooth the edges. To maintain the roundness of the lesion, the radius is edited as 9 pixels. So a larger gap is filled in region and, morphological use of structural elements to close the image.

Input: Skin Lesion Dermoscopy Image ($Image_{RGB}$)
Output: Segmented Binary Image

Step 1: Separate channels of input image to R-channel, B-channel and G-channel images (I_R, I_G, I_B).
Step 2: Calculate the histogram of the image and enhance the intensity values of images from each channel I_R, I_G, I_B by remapping the data values to fill the entire intensity range.
Step 3: Combine three channels of contrast adjusted images as I_{RGB}.
Step 4: Convert I_{RGB} to grayscale image I_{gray}.
Step 5: Compute sum area table by using the equation:

$$I(x,y) = i(x,y)+I(x,y-1)+I(x-1,y)-I(x-1,y-1) \quad (1)$$

where I(x,y) is the value of the pixel at (x,y)
Step 6: Evaluate the sum of intensities over any rectangular area with four array references exactly as in figure 4.
Step 7: Apply average integral filters to image I_{int} with the threshold th filter size.
Step 8: For pixels on I, find an array where each output pixel contains the local entropy value of the 9-by-9 neighborhood around the corresponding pixel in the input image I_{int} to characterize the texture of the input image I_{tex} according to the equation:

-sum(p.*log2(p)) (2)

where p contains the normalized histogram counts.

Step 9: Rescale the grayscale image I_{tex} and convert to binary image I_{BW} with the adaptive threshold value th.

Step 10: A statistical measure of randomness in order to characterize the texture of the input image (which is the entropy value of grayscale image I_{tex}) can be calculated as th.

Step 11: Remove small objects from IBW and perform morphological closing operation.

Step 12: Fill holes in the binary image IBW.

Step 13: To remove dark corners from the segmented binary image, find the region with the centermost region of the image by using the Mahattan distance function between the centroids points of region of interests.

Fig. 5: Eight Symmetric Regions of Binary Lesions

3.2 Feature Extraction and Selection

Feature extraction is a significantly crucial step in classification of skin cancer. To concern in solving a classification problem, features or attributes that can characterize the samples are required. In automated identification the nature of skin lesions, feature extraction is established on the so-called ABCD-rule of dermatology.

The optimum feature set should have implicitly discriminating features as it highly impacts the performance of the classification. ABCD rule known as early signs of melanoma, which comprises the fundamentals for a diagnosis by a dermatologist. ABCD stands for the Asymmetry, Border structure, variegated Color, and the Differential Structures of the skin lesion.

1) A= Asymmetry

One half of the tumor does not correspond to the other.

To examine for the level of symmetry, there are two measures of asymmetry feature i.e. Asymmetry Index (AI) and Lengthening Index (LI).

The uses of A features is to measure the lesion conformation, particularly to the asymmetry of the lesion in accord with the main axes. In this study, both AI and LI are extracted for A feature. The major axis A1 of the lesion is adjusted with its most lengthy diameter, taking through its center; the minor axis A2 is perpendicular to A1 and also leads through the shape center.

2) B = Border Irregularity

The edges are ragged, notched, blurred.

Texture investigation concerns to the brief statement of regions in an image by their texture proportion. Texture analysis seeks to quantitate rational figures distinguished by characterizations such as rough, smooth, silky, or bumpy as a role of the spatial version in pixel saturation. The roughness or bumpiness refers to variations in the intensity values, or gray levels. The texture feature which examines the spatial connectedness of pixels is known as the gray level co-occurrence matrix (GLCM). The boundary sharpness is quantified by the magnitude and variance of the gradient and the GLCM feature at each pixels from the lesion boundary rim.

Rather considering pixels within the lesion boundary, pixels are analyzed to an extended edge. The edge is dilated by 3 pixels, making a 5 pixels broad region centered at the lesion edge. Average Gray Level Co-occurrence Matrix (GLCM) features of the pixels in the lesion extended rim is specified by figuring how a pixel with the intensity (gray-level) value frequently comes in a particular spatial neighborhood to a pixel with the value as shown in figure 4.

3) C = Color Variation

The color (pigmentation) is not distinctive. There are shadows of brown, brown, black, red, white and blue buttons give a blurry look.

The lesion edge diversely abnormality is described in the ABCD rule by separating the edge in 8 symmetric regions as in figure 5. As well as the two main axes A1 and A2, two additional axes are obtained by rotating by 45 degrees these perpendicular axes. Therefore, eight symmetric regions R = 1,.., 8 are generated. For each channel, the mean gradient quantities of the broaden edge pixels (R = 1,.., 8) are computed.

The pigmentation is not uniform so, the features need to measure the color variance rate in the lesion. Physicians usually consider six distinguishable colors in skin lesions: white, red, light and dark brown, blue-gray, and black. To

quantify the color variance in the lesion, and the following measurements can be utilized.

Lesions comprising much of those are greater probably to identify malignant. The lesion color variability can be quantified by reckoning the frequency of those distinctive hues inside a lesion segment. Supposing a pixel in the lesion segment, the closest reference color is found by the Euclidean distance to the pixel color in image.

A hue occurrence count is assumed, one cell per representative hue. For each lesion pixel, the closed representative hue count is indexed by 1. Finally, representative hues counts are normalized by the lesion area, in order to yield the additional feature.

4) D = Diameter of Lesion

Melanomas are usually wider than 1/4 inch (6mm) when diagnosed and they used to grow in timely.

The ABCD rule of dermoscopy changes the D symbol to differential structures since the diameter is, at the stage of diagnosing process, not a reliable parameter. Dermatologists look for the macroscopic structural and vascular parts that are simply perceptible using dermoscopy images. The lesion differential structures are usually identified using texture descriptors. Skin lesions are often more local tissue variance than functioning skin regions that can be used to distinguish between normal functioning and abnormal skin. Four features are extracted maximum, minimum, mean and variance of the pixels intensities amongst the lesion segment to correspond the textural variation in each channel of images.

Irrelevant and unrelated data may be included in the large feature space, and the statement to this question is to apply a feature selection algorithm. To choose the greatly appropriate feature from an image, the method of choosing a subset of related features is executed by getting rid of surplus, irrelevant, noisy data from the original feature set.

The ReliefF Algorithm (RELIEFF), one of the methods for selecting objects based on a filter, is an efficient, simplistic and comprehensive approach to assessing the weight of an object. The weight of the characteristic of the measurement vector is determined taking into account the significance of the function. Based on the results of the relief algorithm, the feature vectors with low weight values are discarded and a new subset of features are selected.

3.3 Feature Extraction and Selection

1) Predicting a lesion to be benign (normal) or malignant (cancerous) is a classification. Given the extracted features, this step is to train a classifier in a training stage and apply the learnt parameters to classify a new skin lesion image. There are a number of classifiers including both parametric and non-parametric type in literature.

2) Cross validation is a method of subdividing the original sample into a learning set that forms a model and determines the predictive model through a series of tests that evaluate it. For k-fold cross-validation, the original sample is randomized into k sub-samples of the same size. For each of the k experiments, the k-1 training and the remaining tests are repeated k times, a single estimate can be obtained by averaging the k results of the convolution. The benefit of k-fold cross-validation is that those samples of records are ultimately utilized for both training and testing.

The classification in the proposed study is carried out using 10 fold cross-validation technique.

Table 1: Evaluation Results for Segmentation of ISBI2016 Dataset

	Active Contour [9]	Iterative Selection [10]	Region Merge [13]	Otsu_ R [14]	Otsu_ RGB [15]	Yen Threshold [16]	Propose
AC	79%	77%	76%	84.9%	80.2%	77%	92.85%
DI	58%	68%	55%	72%	56%	67%	85.58%
JA	46%	56%	43%	57%	45%	58%	80.87%

Table 2: Evaluation Results for Segmentation of PH2 Dataset

	Active Contour [9]	Iterative Selection [10]	Region Merge [13]	Otsu _R [14]	Otsu_ RGB [15]	Yen Threshold [16]	Propose
AC	86%	62%	89%	67%	85%	87%	90.57%
DI	83%	44%	61%	55%	75%	80%	84.81%
JA	76%	33%	43%	45%	60%	72%	79.73%

4. Evaluation

Evaluation Criteria for segmentation are measured the following common segmentation metrics: Accuracy, Sensitivity, Specificity, Dice Coefficient, and Jaccard Index.

Pixel Level Accuracy = (tp+tn)/(tp+fp+tn+fn) (2)

Pixel Level Sensitivity = tp/(tp+fn) (3)
Pixel Level Specificity = tn/(tn+fp) (4)
Dice Coefficient = (2.tp)/(2.tp+fp+tn+fn) (5)
Jaccard Index = tp/(tp+fp+fn) [6]

Where tp- true positive, fp- false positive, tn- true negative, and fn- false negatives at the pixel level.

For the classification task in this study, the accuracy is measured computed as following equation:

Accuracy = (TP+TN) / ((TP+TN+FP+FN)) (7)

where TP, TN, FP, FN, refer to true positive, true negative, false positive, and false negatives, respectively.

The evaluation results for segmentation are discussed in Table 1 and Table 2 for ISBI2016 dataset and PH2 dataset respectively. The proposed segmentation method is evaluated compared with various state-of-the-art segmentation methods such as Active Contour, Iterative Selection, Region Merging, Otsu_R, Otsu_RGB and Yen Thresholding method. The experimental results reported in table 1 and table 2 showed that the proposed method is efficient and effective in skin lesion segmentation. It is found that, applying proposed segmentation method increases the segmentation efficiency.

On the same way, the evaluation results for classification are discussed in Table 3 and Table 4 for ISBI2016 dataset and PH2 dataset respectively. The well-known classifiers such as k-nearest neighbor, support vector machine, ensemble methods are used in classification of pigmented skin lesion. In this work, classifiers are experimented to choose the best classifier and the result shows that random subspace ensemble algorithm outperforms than the other classifiers.

Table 3: TP, FP, TN, FN at the Pixel Level

	Segmented	***GroundTruth***
TP	1	1
FP	1	0
TN	0	0
FN	0	1

Table 4: TP, FP, TN, FN at the Pixel Level

	Predict Benign	***Predict Melanoma***
Benign	TN	FP
Malignant	FN	TP

5. Conclusions

In this study, a model for the segmentation of skin lesions is proposed. Lesion areas are initially segmented using proposed texture based method and various features underlying ABCD rules are extracted to represent segmented lesion areas. Then the classification is performed with different classifiers. Experiments are conducted on our on the ISBI 2016 challenging dataset and PH2 dataset. The proposed segmentation algorithm can provide accurate segmentation results in order to use in segmentation task of skin lesion and the proposed feature is robust according to the weight value resulted from feature selection algorithm. In classification process, random subspace ensemble algorithm with feature data optimized by relief algorithm give better classification results for benign or melanoma cancer classification. The current research work address only to the classification of pigmented skin lesion as either benign or malignant melanomas skin cancer. Therefore, classification of various pigmented skin lesions such as Melanomas, Nevus, BCC, Seborrheic Keratoses, etc would be studied as the future research work.

Acknowledgments

I would like to acknowledge my heartfelt thanks to the editors of IJCSN organization for partial reduction of this research journal.

Table 5: Classification Accuracies of PH2 and ISBI2016 Dataset

	No Dimension Reduction		***Dimension Reduced Subset by PCA***	
	PH2	***ISBI 2016***	***PH2***	***ISBI 2016***
kNN	89.0%	80.9%	84.5%	81.1%
SVM	89.5%	80.9%	84.5%	80.9%
Random Subspace Ensemble	**90.0%**	81.1%	**86.5%**	80.9%

References

[1] David Gutman1y, Noel C. F. Codellay, Emre Celebi, Brian Helba, Michael Marchetti, Nabin Mishra, Allan Halpern, "Skin Lesion Analysis toward Melanoma Detection", Proceedings of the International Symposium on Biomedical Imaging (ISBI), arXiv:1605.01397v1 [cs.CV] 4 May 2016.

[2] Lequan Yu, Hao Chen, Qi Dou, Jing Qin, and Pheng-Ann Heng, "Automated Melanoma Recognition in Dermoscopy Images via Very Deep Residual Networks", IEEE Transactions on Medical Imaging, DOI 10.1109, April 2016.

[3] Khalid Eltayef, Yongmin Li and Xiaohui Liu, "Knowledge Transfer for Melanoma Screening with Deep Learning", 2016 International Conference on Communication, Image and Signal Processing (CCISP 2016).

[4] Oliveira R.B., Pereira A.S., Tavares J.M.R.S. (2018) "Pattern Recognition in Macroscopic and Dermoscopic Images for Skin Lesion Diagnosis". In: Tavares J., Natal Jorge R. (eds) VipIMAGE 2017. ECCOMAS 2017. Lecture Notes in Computational Vision and Biomechanics, vol 27. Springer, Cham.

[5] Bi, Lei & Kim, Jinman & Ahn, Euijoon & Feng, David Dagan Feng & Fulham, Michael, "Semi-automatic skin lesion segmentation via fully convolutional networks", 561-564. 10.1109/ ISBI. 2017. 7950583.

[6] D. Gutman, et al., "Skin Lesion Analysis toward Melanoma Detection: A Challenge at the International Symposium on Biomedical Imaging (ISBI) 2016, hosted by the International Skin Imaging Collaboration (ISIC)," arXiv preprint arXiv:1605.01397, 2016.Li, Yuexiang & Shen, Linlin., Skin Lesion Analysis Towards Melanoma Detection Using Deep Learning Network. 2017.

[7] Capdehourat G., Corez A., Bazzano A., and Mus P., "Pigmented Skin Lesions Classification Using Dermatoscopic Images", CIARP 2009, LNCS 5856, pp. 537–544, Springer-Verlag Berlin Heidelberg 2009.

[8] Lee T, Ng V, Gallagher R, Coldman A, McLean D. "DullRazor: A software approach to hair removal from images. Computers in Biology and Medicine", 1997;27:533-543.

[9] Bi, Lei & Kim, Jinman & Ahn, Euijoon & Feng, David Dagan Feng & Fulham, Michael, "Semi-automatic skin lesion segmentation via fully convolutional networks", 561-564. 10.1109/ ISBI. 2017. 7950583.

[10] D. Gutman, et al., "Skin Lesion Analysis toward Melanoma Detection: A Challenge at the International Symposium on Biomedical Imaging (ISBI) 2016, hosted by the International Skin Imaging Collaboration (ISIC)," arXiv preprint arXiv:1605.01397, 2016.Li, Yuexiang & Shen, Linlin., Skin Lesion Analysis Towards Melanoma Detection Using Deep Learning Network. 2017.

[11] Capdehourat G., Corez A., Bazzano A., and Mus P., "Pigmented Skin Lesions Classification Using Dermatoscopic Images", CIARP 2009, LNCS 5856, pp. 537–544, Springer-Verlag Berlin Heidelberg 2009.

[12] Lee T, Ng V, Gallagher R, Coldman A, McLean D. "DullRazor: A software approach to hair removal from images. Computers in Biology and Medicine", 1997;27:533-543.

[13] Bi, Lei & Kim, Jinman & Ahn, Euijoon & Feng, David Dagan Feng & Fulham, Michael, "Semi-automatic skin lesion segmentation via fully convolutional networks", 561-564. 10.1109/ ISBI. 2017. 7950583.

[14] D. Gutman, et al., "Skin Lesion Analysis toward Melanoma Detection: A Challenge at the International Symposium on Biomedical Imaging (ISBI) 2016, hosted by the International Skin Imaging Collaboration (ISIC)," arXiv preprint arXiv:1605.01397, 2016.Li, Yuexiang & Shen, Linlin., Skin Lesion Analysis Towards Melanoma Detection Using Deep Learning Network. 2017.

[15] Capdehourat G., Corez A., Bazzano A., and Mus P., "Pigmented Skin Lesions Classification Using Dermatoscopic Images", CIARP 2009, LNCS 5856, pp. 537–544, Springer-Verlag Berlin Heidelberg 2009.

[16] Lee T, Ng V, Gallagher R, Coldman A, McLean D. "DullRazor: A software approach to hair removal from images. Computers in Biology and Medicine", 1997;27:533-543.

[17] Ammara Masood, Adel Ali Al-Jumaily, "Computer Aided Diagnostic Support System for Skin Cancer: A Review of Techniques and Algorithms", International Journal of Biomedical Imaging, vol. 2013, Article ID 323268, 22 pages, 2013. https://doi.org/10.1155/2013/323268.

[18] I. Maglogiannis and C. N. Doukas,, "Overview of Advanced Computer Vision Systems for Skin Lesions Characterization", IEEE Transactions on Information Technology in Biomedicine, vol. 13, no. 5, pp. 721-733, doi: 10.1109/TITB.2009.2017529, Sept. 2009.

[19] Qaisar Abbas, M. Emre Celebi, Irene Fondo´n G. and Muhammad Rashid, "Lesion border detection in dermoscopy images using dynamic programming," Skin research and technology : official journal of International Society for Bioengineering and the Skin (ISBS) [and] International Society for Digital Imaging of Skin (ISDIS) [and] International Society for Skin Imaging (ISSI). 17. 91-100. 10.1111/j.1600-0846.2010.00472.x.

[20] Konstantin Korotkov, Rafael Garcia, "Computerized analysis of pigmented skin lesions: a review", Artificial Intelligence in Medicine, 56(2), 69–90. doi:10.1016/ j.artmed. 2012.08.002.

First Author Nay Chi Lynn received her Bachelor Degree of Computer Science with Honors and earned her Master Degree of Computer Science from University of Computer Studies, Mandalay in 2007 and in 2009 respectively. From 2016 to 2017, she was studying as a research student at University of Miyazaki funded by Miyazaki Prefectural Government for image processing research in livestock industry. She is currently studying her Ph.D. degree in Information Technology currently in University of Computer Studies, Mandalay.