Automatic detection of translucency using a deep learning method from patches of clinical basal cell carcinoma images

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Abstract— **Translucency, defined as a jelly-like appearance, is a common clinical feature of basal cell carcinoma, the most common skin cancer. The feature plays an important role in diagnosing basal cell carcinoma in an early stage because the feature can be observed readily in clinical examinations with a high specificity of 93%. Therefore, translucency detection is a critical component of computer aided systems which aim at early detection of basal cell carcinoma. To address this problem, we proposed an automated method for analyzing patches of clinical basal cell carcinoma images using stacked sparse autoencoder (SSAE). SSAE learns high-level features in unsupervised manner and all learned features are fed into a softmax classifier for translucency detection. Across the 4401 patches generated from 32 clinical images, the proposed method achieved a 93% detection accuracy from a five-fold cross-validation. The preliminary result suggested that the proposed method could detect translucency from skin images.**

Keywords—Translucency, deep learning, stacked sparse autoencoder, basal cell carcinoma

I. INTRODUCTION

Basal cell carcinoma (BCC) is the most common type of skin cancer among the white populations in the world[1]. Only in the United States alone, more than 4 million patients are diagnosed with skin cancer annually and 80% of them are BCC[4,14]. In addition, there is an increasing trend of the disease.[2-5]. The increasing rates is about 5% in Europe and is about 2% in the United States[3]. Despite the fact that BCC rarely causes mortality, the malignancy will destroy extensively the surrounding tissues and damage the skin structure aggressively in advanced stages[6-8]. Therefore, early detection of BCC is important for disease management. The initial recognition of skin cancer strongly relies on visual examination by physicians, following by a confirmation diagnosis based on biopsy and histological examination[9]. However, many research studies have been focusing on the development of computer-aided systems for detecting skin cancer automatically in order to relieve the pressure caused by the rapid growth of the diseases and the limited medical resources. These computerized systems may lead to a higher diagnostic accuracy for early stages as well.

Translucency, defined as a jelly-like appearance, is an important characteristic feature of BCC. It is an optical phenomenon generated by the cancerous tumor[10-11]. Translucency plays an important role in the diagnosis of BCC because the feature can be readily observed in clinical examinations with a high specificity of 93% [13]. Therefore, detecting translucency is a key function for computer aided systems aimed at discriminating BCCs from benign skin conditions and other types of skin cancers as well.

Previous works in automatic analysis of translucency in BCC have all been done by using dermoscopy images. Demorscopy is a non-invasive tool for skin cancer detection that enables the visualization of subsurface structures and patterns[15]. In [11], classification of BCC or non-BCC is done through using color and histogram measures of translucency. In [12], Stoecker et al. detected translucent areas from BCC using a texture-based segmentation method. However, clinical images, taken by color digital cameras, are the most convenient method for capturing diagnostic features. Unlike dermoscopy, which are often pressed against a skin lesion and lead to distortion of the skin surface and color appearance, clinical images are captured free from skin contact, and, hence, free of distortion of the translucency feature. Thus, it is important to investigate techniques using for automatic detection of translucency from clinical images. However, detecting translucency from BCC using clinical image is a challenging task because of different zooming levels, lighting conditions and imaging angles[9]. Therefore, comprehensive and powerful methods are needed, and in this study, we will apply a deep learning approach to manage these difficulties.

In this paper, we present a method based on a stacked sparse autoencoder (SSAE) for detecting translucency from patches of clinical BCC images, which were captured using a digital color camera in a contact free manner. SSAE is an unsupervised learning method with a fully connected architecture. The remaining of the paper is organized as followes: In section II, we describe the proposed framework used in this research. Section III presents the dataset used and the experimental results. Finally, section IV concludes the paper with a suggestion of future works.

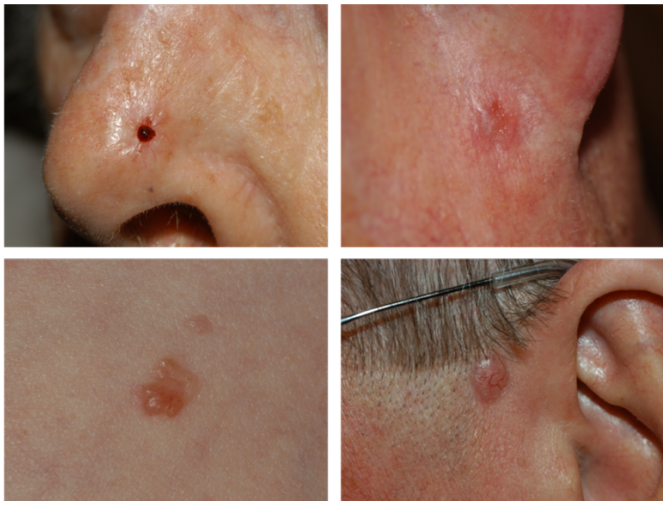

Figure 1: Examples of clinical basal cell carcinoma images showing translucency

II. METHOD

We proposed a SSAE-based framework for automatic translucency detection. SSAE is an unsupervised learning model which can learn high-level features directly from unlabeled data. Also, SSAE can perform pixel-level learning. In particular, SSAE are applied to patches of clinical skin images. Using patches have two advantages. Firstly, patches will increase the number of data points for the learning process. Secondly, patches will decrease the dimensionality of input data so that the fully connected network can be carried efficiently. The diagram of proposed method is shown in Figure 2, and the major components of the method will be described below.

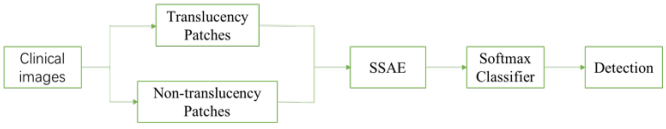

Figure 2: Diagram of proposed framework

A. Sparse autoencoder

An autoencoder is a neural network which learns high-level features in an unsupervised manner as shown in Figure 3. It reconstructs the input data at the output layer in order to discovery a hidden feature representation of the input data. Therefore, the autoencoder attempts to find the function $h_{W,b}(x) \approx x$ which will reconstruct the input x as $\tilde{x}$, where W is the weight of each hidden neuron and b is the bias. A sparse autoencoder is a type of autoencoder with a sparsity constraint which will be discussed below. From Applying a backprobagation algorithm to train the sparse autoencoder, the optimal (W,b) will be learned by minimizing the discrepancy between the input x and its reconstruction $\tilde{x}$. The cost function of training a sparse autoencoder is:

$$J_{SAE} = \frac{1}{N}\sum_{n=1}^{N}\sum_{i=1}^{H}(x_{in} - \widetilde{x_{in}})^2 + \eta||\mathrm{W}||^2 + \beta\sum_{j=1}^{H} KL(\rho||\widetilde{\rho_j}),$$

where the first term is the mean square error term which describes the error between the input data and its reconstruction. N is the number of the input data and the H is the number of hidden neurons. The second term is a weight decay term which aims to decrease the magnitude of the overall neuron weight in order to avoid overfitting. η is the attenuation coefficient of the weigh decay. The third term is the sparsity constraint term which constrains the average activation value of each hidden neuron to be close to zero. ρ is the desired activation, a free sparsity parameter, which determines the proportion of neurons being active and ρ' is the average activation of j^{th} hidden neuron. The aim of sparse constrain is to minimize ρ_j using Kullback-Leibler (KL) divergence, $KL(\rho||\rho_j)$, between ρ_j and ρ. KL measures the difference of two distributions with the formulation: $KL(\rho||\rho_j) = \rho log\frac{\rho}{\rho_j} + (1-\rho)log\frac{1-\rho}{1-\rho_j}$. β controls the weight of this penalty term.

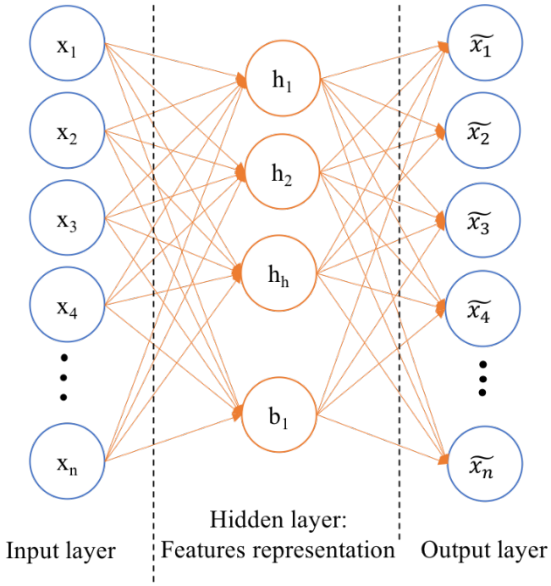

Figure 3: Structure of an autoencoder

B. *High-level features learning through SSAE*

The stacked sparse autoencoder is a neural network consisting of multiple layers of sparse autoencoders in which features are learned in a layer-by-layer manner. The output of each layer is wired to the input of the successive layer. For the purpose of detecting translucency from BCC in clinical images, we considered to use a two-layer sparse autoencoder. The architecture of the translucency detection framework is demonstrated in Figure 4.

As Figure 4 shows, the color input patches (32 x 32 x 3) are fed into the first layer that are transformed to the feature representations h_1 as the result of first layer training. Then the second layer are fed with the new feature representations to learn the high-level features h_2. Finally, the high-level features learned from SSAE acts as the input to the softmax classifier for translucency detection.

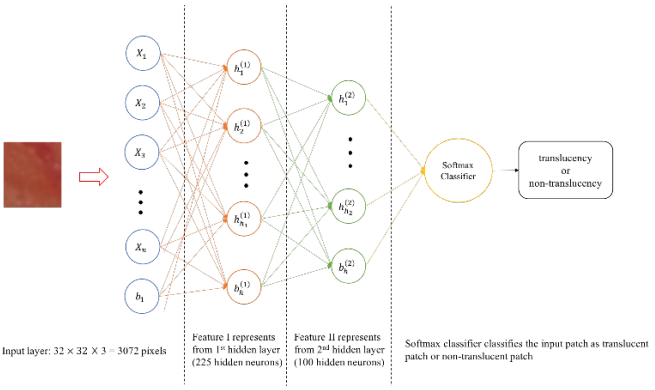

Figure 4: The proposed framework of the stacked sparse autoencoder and softmax classifier for detecting translucency

C. *Translucency detection through softmax classifier*

Softmax classifier is a supervised learning method which is a generalization of Logistic Regression. Softmax categorizes the newly learned features into one of the label classes which has the highest probabilities. For instance, the classifier produces the probability of the presence of translucency in an input patch t=1 as follows:

$$P(t = 1|z) = \frac{1}{1 + e^{-z}}$$

where z is the learned high-level feature.

And the softmax classifier is trained by minimizing the cross-entropy between the estimated class q and the true class p:

$$H = \frac{1}{N}\sum_{j=1}^{N}\sum_{i=1}^{C} p_{ij} log q_{ij} + (1 - p_{ij})\, log\,(1 - q_{ij}),$$

where N is the total number of inputs and C is the number of classes. In our case, C is 2.

For training the softmax classifier, the high-level features learned from SSAE, which regard as the input, are fed into the classifier with the associate labels since softmax learns in supervised manner. Then softmax classifier will ready for detecting translucency according to the calculated probability of patches contain translucency.

III. Experiment

A. *Dataset*

The dataset we used consists of 32 clinical images of basal cell carcinoma collected from 32 patients in Vancouver Skin Care Centre. (See Figure 1.) The images are 3008 × 2000 pixels. The targeted lesion is near the center of the image with different sizes. All cases were confirmed by histopathological examinations.

Translucent areas from these images were segmented by an expert dermatologist (D.I.M.). For the purpose of detecting translucency better, we created region of interest(ROI) using bounding box. The size of each ROI images depends on the size of targeted lesion in original clinical image. Some examples were shown in Figure 5. The size of ROI image in (a) is 492 × 512 and size of ROI image in (b) is 1024 × 1228. Then we divided these ROI images into non-overlapped patches. A patch contains translucency was labeled as 1 and 0 for non-translucency. The total number of patches were 4401; there were 797 translucent patches and 3604 non-translucent patches. Examples of extracted patches with and without translucency is given in Figure 6.

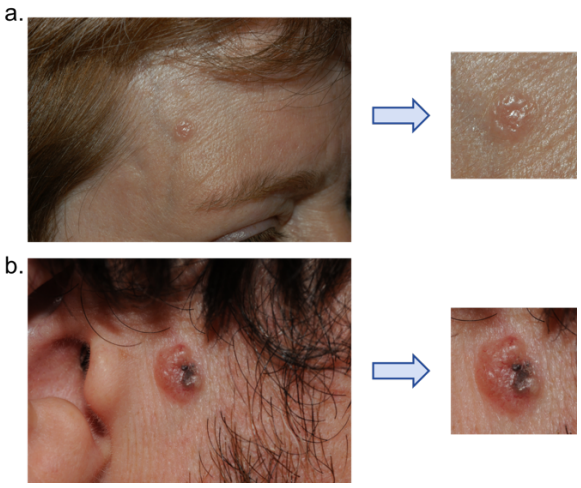

Figure 5: Examples of creating ROI images

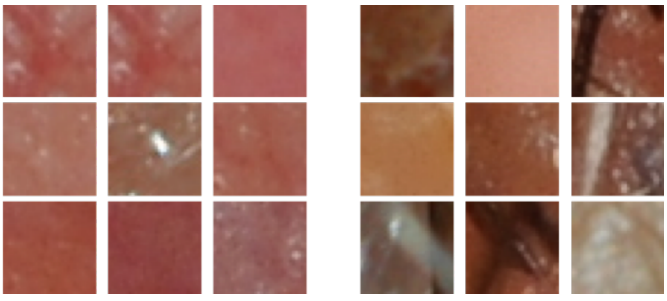

Figure 6: Examples of patches: translucent patches are in the left side and non-translucent patches are in the right side

B. *Parameters setting*

In the experiment, patch size was chosen as 32 × 32 pixels. The size of input for SSAE was 32 × 32 × 3 = 3072. Because all

the images are RGB, all three color channels are inputted to the network simultaneously. For successive layers of SSAE, the number of hidden nodes in first and second layer were chosen h_1 = 225 and h_2 = 100. For two control parameters, the sparsity parameter β was set to 4 and the weight decay parameter η was set to 0.001. ρ which is the desired activation parameter was set to 0.05. Initialization of bias and the weight of each neuron are random at the beginning of training.

C. Results

Applying the proposed SSAE network with a five-fold cross-validation to the patches, the result of translucency detection is illustrated in Table1. The SSAE method achieved an accuracy of 0.93, a sensitivity of 0.77 and a specificity of 0.971. The Receiver Operating Characteristic Curve (ROC) of the proposed method is shown in Figure 7. From the experiment results, we demonstrated that SSAE work well in detecting translucency in patches of clinical images. All experiments were performed on a PC (Intel core i7 with 16GB RAM) and Geforce GTX NVIDIA Graphics processor Unit.

	Sensitivity	Specificity	PPV	PPN	Accuracy
SSAE+SMC	0.77	0.971	0.873	0.942	0.93

Table 1: Result of translucency detection

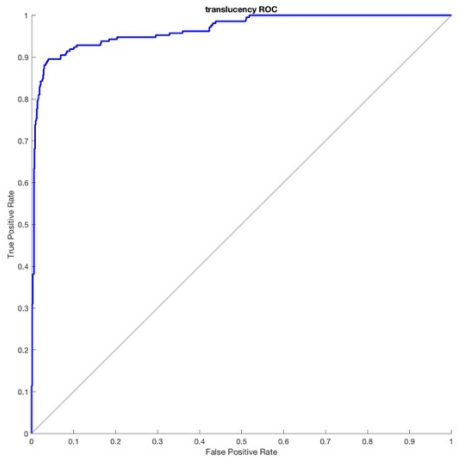

Figure 7: the ROC curve for translucency detection of proposed method

IV. Conclusion

In this paper, we present an unsupervised deep learning framework based on a stacked sparse autoencoder for translucency detection from patches of clinical BCC images. This method achieved a detection accuracy of 93%, with a specificity and sensitivity of 97.1% and 77%, respectively. The results demonstrated that the method appears to be able to detect translucency from skin patches. For the next step of our study, we plan to expand this method to infer translucency in a skin lesion according to the skin patches of the lesion. And then we will build a computer-aided diagnosis system for BCC based on translucency and other diagnostic features.

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References

[1] Diepgen and V. Mahler, "The epidemiology of skin cancer", *British Journal of Dermatology*, vol. 146, no. 61, pp. 1-6, 2002.

[2] A. Arits, M. Schlangen, P. Nelemans and N. Kelleners-Smeets, "Trends in the incidence of basal cell carcinoma by histopathological subtype", *Journal of the European Academy of Dermatology and Venereology*, vol. 25, no. 5, pp. 565-569, 2010.

[3] Verkouteren, J. A. C., K. H. R. Ramdas, M. Wakkee, and T. Nijsten, "Epidemiology of basal cell carcinoma: scholarly review", British *Journal of Dermatology,* vol. 177, no. 2, pp. 359-372, 2017.

[4] H. Rogers, M. Weinstock, S. Feldman and B. Coldiron, "Incidence Estimate of Nonmelanoma Skin Cancer (Keratinocyte Carcinomas) in the US Population, 2012", *JAMA Dermatology*, vol. 151, no. 10, p. 1081, 2015.

[5] Rubin, Adam I., Elbert H. Chen, and Désirée Ratner, *"Basal-Cell Carcinoma", New England Journal of Medicine,* vol. 354, no. 7, pp. 769-771, 2006.

[6] S. Hakverdi, D. Balci, C. Dogramaci, S. Toprak and M. Yaldiz, "Retrospective analysis of basal cell carcinoma", *Indian Journal of Dermatology, Venereology, and Leprology*, vol. 77, no. 2, p. 251, 2011.

[7] Zargaran M, Moghimbeigi A, Monsef A, Teimourian H, Shojaei S. "A Clinicopathological Survey of Basal Cell Carcinoma in an Iranian Population", *Journal of Dentistry*, vol. 14, no.4, pp. 170-177, 2013.

[8] Rippey, J. J, "Why classify basal cell carcinomas?", Histopathology, vol. 33, no. 4, pp. 393-393, 1998.

[9] A. Esteva, B. Kuprel, R. Novoa, J. Ko, S. Swetter, H. Blau and S. Thrun, "Corrigendum: Dermatologist-level classification of skin cancer with deep neural networks", *Nature*, vol. 546, no. 7660, pp. 686-686, 2017.

[10] W. Stoecker, I. Kolm, H. Rabinovitz, M. Oliviero, J. Xu and J. Malters, "Semitranslucency in Dermoscopic Images of Basal Cell Carcinoma", *Archives of Dermatolo*gy, vol. 145, no. 2, 2009.

[11] Stoecker, William V., Kapil Gupta, Bijaya Shrestha, Mark Wronkiewiecz, Raeed Chowdhury, R. Joe Stanley, Jin Xu et al., "Detection of basal cell carcinoma using color and histogram measures of semitranslucent areas", *Skin Research and Technology*, vol. 15, no. 3, pp. 283-287, 2009.

[12] S. Kefel, S. Pelin Kefel, R. LeAnder, R. Kaur, R. Kasmi, N. Mishra, R. Rader, J. Cole, Z. Woolsey and W. Stoecker, "Adaptable texture-based segmentation by variance and intensity for automatic detection of semitranslucent and pink blush areas in basal cell carcinoma", *Skin Research and Technology*, vol. 22, no. 4, pp. 412-422, 2016.

[13] Popadic, Mirjana. "Statistical evaluation of dermoscopic features in basal cell carcinomas." *Dermatologic Surgery* 40, no. 7, pp. 718-724, 2014.

[14] N. Eisemann, A. Waldmann, A. Geller, M. Weinstock, B. Volkmer, R. Greinert, E. Breitbart and A. Katalinic, "Non-Melanoma Skin Cancer Incidence and Impact of Skin Cancer Screening on Incidence", *Journal of Investigative Dermatology*, vol. 134, no. 1, pp. 43-50, 2014.

[15] G. Argenziano and H. P. Soyer, "Dermoscopy of pigmented skin lesions – a valuable tool for early," *The Lancet Oncology*, vol. 2, no. 7, pp. 443–449, 2001.