SMART FACIAL SKINCARE PRODUCTS USING COMPUTER VISION TECHNOLOGIES

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***Abstract*— Acne is a skin issue that plagues many young people and adults. Even if it is cured, it leaves acne spots or acne scars, which drives many individuals to use skincare products or undertake medical treatment. On the contrary, the use of inappropriate skincare products can exacerbate the condition of skin. In view of this, this work proposes the use of computer vision technology to realize a new business model of facial skin care products based on the concept of unmanned stores. Skin care products recommendation system provides consumers with professional skin analysis through skin type classification and acne detection to recommend skin care products that improve skin issues of consumers finally. Experimental results show that the comparison of the skin type classification accuracy is the highest.**

I. INTRODUCTION

Since most people have not received professional medical knowledge training, if they use inappropriate products at will, they will easily become self-defeating and make the skin condition more serious, which will cost much money and time to remedy, and even lead to repeated skin issues such as acne. Acne is also called pimples, and the main cause of acne is excessive sebum secretion, which tends to occur in places with more sebaceous glands. According to the Global Acne Market Report for 2016-2026 [1], acne is one of the most common diseases for which dermatologists provide treatment assistance and more than 90% of the world's population suffer from acne symptoms.

The sales channels of skin care products are mainly physical stores, which can be further divided into open drugstores and skin care products counters. Open drugstores have a leisure and free shopping environment, but the advice obtained by consulting the store staff may not be rigorous, and skin care products counters are prone to frequent sales promotion by the clerks, which reduces the clients' willingness to purchase. Online shopping products often contain defects and counterfeit products, which are prone to risk of harm. The recent prevalence of unmanned stores has many similarities with the above factors. The unmanned automated business model can effectively reduce labor costs, cash exchanges and contact between cashiers and customers to maintain hygiene and safety and provide better personalized services. According to The Power of Artificial Intelligence for Cosmetics Brands [2], personalized recommendation system has become a future trend, which not only stimulates more consumption power, but also strengthens the relationship with consumers. In view of this, this work proposes to realize a new business model of facial skin care products with Computer Vision (CV) technology. In addition to facial analysis of skin type classification and acne detection, recommending for skin care products are also provided.

The skin care products recommendation system in this work adopts Machine Learning (ML) and Deep Learning (DL) methods. Compared with traditional CV technologies, it improves the issue of environmental constraints and low recognition rate. In recent years, many studies have been adopting DL methods to discuss skin quality as well. As the symptoms of various skin diseases are similar, it is difficult for doctors to distinguish with naked eyes. Junayed *et al.* [3] use Convolutional Neural Network (CNN) to develop Deep Residual Neural Network (DRNN), which can identify five types of acne to assist doctors in diagnosis. As skin cancer is steadily increasing around the world, preventive medicine is also becoming increasingly important. Vesal *et al.* [4] use U-Net [5] to identify skin lesions before skin cancer, and the experimental results reached 93% on the Sensitivity (SE) target. Hameed *et al.* [6] use CNN and Support Vector Machine (SVM) [7] to identify skin diseases with an accuracy rate of 90%. The above studies show that the features obtained by CNN can enhance the classification effect of a variety of skin diseases. Due to the increasing types of skin diseases, there have been more and more studies discussing skin pigmentoma in recent years. Goyal *et al.* [8] identifies skin melanoma by Region-based Convolutional Neural Network (R-CNN) [9], and the accuracy rate reached 98%. Reference [10] use Deep Convolutional Neural Network (DCNN) and the sub-network in the encoder/decoder architecture to identify pigmented tumors on the skin surface, and the accuracy rate reached 96%.

The remainder of this paper is organized as follows. We describe proposed method in Section 2, present experimental results in Section 3, and draw conclusions in Section 4.

II. PROPOSED METHOD

Skin care products recommendation system is divided into two parts: skin type classification and acne detection. It is implemented by combining multi-feature processing with ML classification technology and DL semantic segmentation [11] technology. Finally, according to the analysis of skin type and acne status, facial skin care products are recommended to consumers. The flowchart of the skin care products recommendation system is shown in Fig. 1.

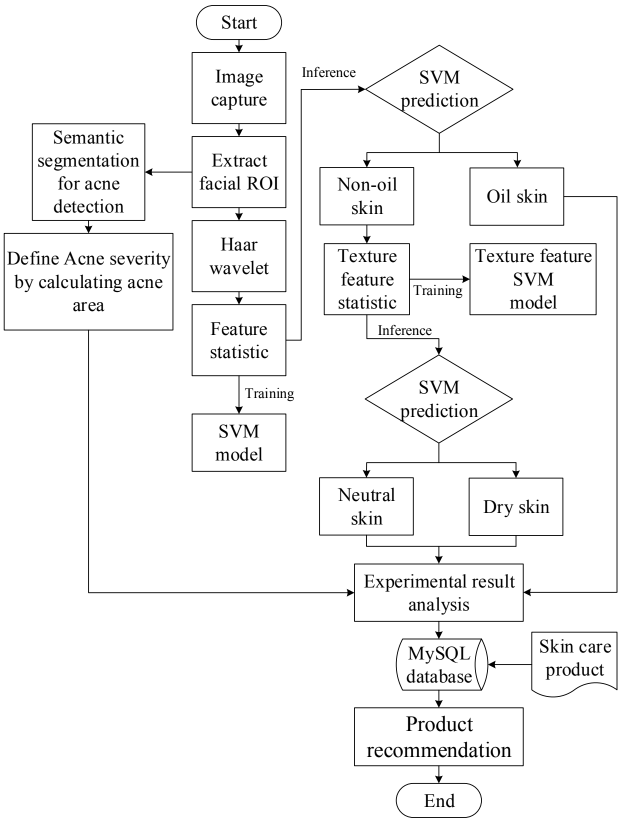


Fig. 1. Flowchart of skin care products recommendation system.

A. Image capture and extract Region of Interest (ROI)

This system uses Logitech's C310 camera to capture facial images, and then uses the cross-platform CV library (Open Source Computer Visual Library, OpenCV) facial recognition model to detect facial regions in the image. Facemark [12] is then used to identify 68 features of the face, and at the same time marks the output on the display screen for the user to confirm whether the facial contour has been captured correctly. Then, it uses the four areas including left and right cheeks, forehead and chin as ROI image which is prone to acne and oily, and finally outputs the ROI captured image to skin type classification and acne detection.

B. Skin type classification

In skin type classification part, the input ROI image is converted into a gray-scale image first, and then a two-level Haar [13] DWT is performed on the gray-scale image to obtain seven sub-bands. The reason for choosing Haar as the wavelet transform is that Haar wavelet is orthogonal and double-orthogonal simultaneously. Besides, the spatial resolution is low and the quality is high [14]. According to the seven sub-bands after Haar wavelet transformation, the system uses the LL band coefficients in the two-level transformation [15] to calculate them in histogram, and then uses the cumulative number of the four selected intervals [16] in the histogram as parameters. The selected interval includes [110, 120), [120, 130), [180, 190) and [190, 200), and these four parameters are used in the classification of the first stage of skin type classification.

The second stage of classification is to use the ROI image transformed by Haar wavelet to calculate texture features. According to the distance and angle between two pixels in the image, the cumulative number with the same gray level is calculated and implemented by a co-occurrence matrix. Then, based on the co-occurrence matrix [16], Contrast is calculated as shown in (1); Inverse Difference Moment (IDM) is calculated as shown in (2); Entropy is calculated as shown in (3), and they are finally used for the second stage of classification.

$$Contrast = \sum_{n=0}^{Eg-1} n^2 \times \left\{ \sum_{i=1}^{Eg} \sum_{j=1}^{Eg} p(i,j \mid d,0°) \right\} \left| i+j=1 \right| \tag{1}$$

$$\text{IDM} = \sum_i \sum_j \frac{1}{1+(i-j)^2} \times p(i,j \mid d,0°) \tag{2}$$

$$Entropy = -\sum_i \sum_j p(i,j \mid d,0°) \times \log\{p(i,j \mid d,0°)\} \tag{3}$$

In the skin type classification part, the linear SVM is used to classify the skin type. According to the four sub-band parameters after statistics as the first type of feature, the oily and non-oily skin are first distinguished, and then the texture feature is used as the second type of feature to distinguish neutral skin and dry skin from non-oily skin. The advantage of SVM is that it can classify from explicit features and only takes a small number of samples to train the classification model, so this model is used as the basis for classification.

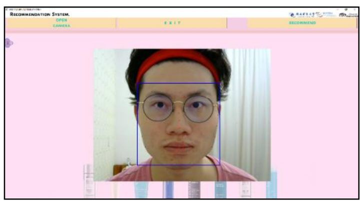
C. Acne detection

In the part of acne detection, the captured ROI image is input to the DeepLab-v3+ [17] model for pixel-level prediction. First, the encoder adopts the Atrous Spatial Pyramid Pooling (ASPP) architecture and calculates the multi-dimensional features with different convolution rates, and then performs bilinear upsampling on the acquired features and concatenate them with bottom layer features which have the same spatial resolution. After concatenation, convolution is used to refine the features, and then a bilinear upsampling is performed. In order to reduce the computational complexity, this system separates the standard convolution into a depth separable convolution, and performs spatial convolution independently for each layer of input channel, and pointwise convolution is used for combining output of convolution.

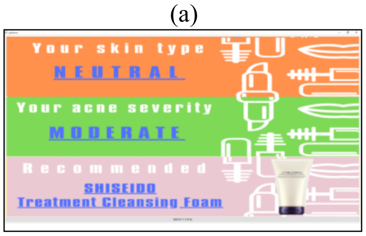
In the part of acne statistics, we analyze the segmented images, and calculate the proportion of the acne area occupying the ROI image area. Finally, the user's acne severity is determined according to the calculated acne ratio value and the resulting image is divided into areas of mild, moderate and serious acne. The higher the ratio, the more serious the issue is.

D. User interface

The user interface of skin care products recommendation system is shown in Fig. 2. The user can determine whether the facial contour is accurately captured according to the screen, and then press the recommendation button, as shown in Fig. 2(a), and view the analytical results and recommended results as shown in Fig. 2(b).



(a)



(b)

Fig. 2. Skin care products recommendation system: (a) Detection interface and (b) result interface.

III. EXPERIMENTAL RESULTS

The accuracy of skin type classification in this work is shown in Table 1 Through cooperation with dermatologists, systematic tests are carried out from the perspective of medical profession, and the doctors' professional advice on various types of skin is carried out. The skin type classification accuracy rate is the comparison statistics between the results of this work and the results diagnosed by the doctors.

Table 1. Accuracy of skin type classification.

Method	Oily	Neutral	Dry
This work	83%	94%	77%
J. Lee *et al*. [16]	82%	85%	83%

IV. CONCLUSIONS

This work proposes the use of CV technology to realize a new business model of facial skin care products. The difference between this work and the previous literature is that this work proposes a novel system based on the concept of unmanned stores. In addition to facial analysis of skin type classification and acne detection, recommending for skin care products are also provided. The experimental results show that the comparison of the skin type classification accuracy is the highest.

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