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A Novel Deep Neural Network for Facial Beauty Improvement

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Abstract. This study delves into how to combine deep learning and fuzzy logic reasoning to evaluate facial aesthetics and provide targeted makeup recommendations. To further optimize the prediction results, we adopted the BLS method to correct the prediction residuals generated by ResNet-50. Specifically, the predicted appearance score can be expressed as $score = p + \delta$, where p is the predicted result and δ represents the predicted residual of the system. After determining the beauty rating, we further studied four different makeup combinations (x_1, x_2, x_3, x_4). Moreover, we introduced fuzzy logic reasoning, defined fuzzy sets and fuzzy relationships, and established membership matrices for each makeup combination. The results of these fuzzy logical reasoning allow us to set a value range of m, n for each makeup method. Based on these reasoning results, we have come up with makeup recommendations for different facial aesthetics. Performance our system with the data collected from internet (accuracy of the calculation = 93.26%), from one volunteer (accuracy of the calculation = 98.14%) and from the both with different makeup skills (accuracy of the calculation = 95.63%) demonstrated that the visual sensing problem is feasible and will be a novel direction for the related engineering applications.

Keywords: system, facial beauty, makeup skills, residual learning, fuzzy computation

1 Introduction

Facial attractiveness, also known as the attractiveness of a face, has always played an important role in social life [1-5]. As a component of first impression, appearance has a significant impact on individuals in the workplace, marriage market, and other aspects [6-10]. However, traditional facial appearance evaluation methods have certain limitations, mainly relying on manually designed feature extractors and classifiers, which limit their accuracy [11-13]. Deep learning, as an end-to-end learning method, has broad application prospects in facial beauty assessment [14-20]. Deep learning can automatically learn image features by constructing multi-layer convolutional neural networks, transforming raw image data into more abstract expressions, and improving the accuracy of facial evaluation [20-25]. Unlike traditional methods, deep learning methods do not require manual design of feature extractors and classifiers, but rather evaluate based on learned features, with higher generalization ability [26]. This enables deep learning methods to better adapt to facial appearance assessment tasks of different groups and age groups, improving their practicality [26, 27].

Makeup products manufacturers can understand the key factors that affect their appearance by deep learning, and develop more targeted product and promotional strategies [28]. Social networking platforms, especially those centered around stranger socializing, such as blind date apps, can evaluate the appearance of user photos through deep learning and provide better social matching services [29]. In addition, deep learning plays an important role in photo beautification applications, helping users enhance their appearance [30]. Considering the widespread application of deep learning in related fields, we believe that it can also be applied in makeup guidance [31]. With

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the continuous development of deep learning technologies, we can expect more innovations and applications to emerge, providing more possibilities for social development and individual needs [32]. Deep learning will continue to play a crucial role in the field of facial evaluation and become one of the important areas for future research and application [33]. The previous studies focused on the applications of deep learning in facial beauty assessment [34]. These studies focus on evaluating the accuracy and generalization ability of deep learning models, which helps people better understand and apply the concept of appearance [35]. It is necessary to further construct a deep learning system for accurate and real-time makeup recommendations by analyzing the users' facial features [36].

Based on this motivation, the objectives of this paper are to (1) propose an intelligent visual sensing problem on makeup skills – how machines to learn-to-recommend makeup skills; (2) analyze the problem under the meta-learning framework with a deep residual learning model; (3) construct a deep learning system with fuzzy reasoning strategies for an accurate cognition of the users' facial features and real-time makeup recommendations. The organization of the whole manuscript is as follows. In Section 2, the structure of the proposed system, along with the data acquisition processes, are explained. For a better understanding of the system, some details for the deep residual learning, beauty score calculation and learning to learn makeup skills are also explained. In Section 3, the experimental results and analyses are presented, including the quickly connected system, the improved beauty and scores from fuzzy computation are shown and discussed. Recommendations of makeup methods are generated. A comparison with existing systems is carried out at the end of the paper for the cross validation.

2 Materials and Methods

2.1 Data Collection

We collected 10380 photos from the makeup videos of 18 makeup skills on the Internet to link FBP with makeup skills. Then, we collected 10238 photos from the makeup videos of three volunteers for a cross validation. Both Internet data and the SCUT-FBP5500_with_Landmarks have included people of different facial skin color, which generalizes the prediction before proceeding to makeup combinations. The image pixels in the SCUT-FBP dataset are generally higher, with the lowest pixel being 350 x 350 pixels. This dataset contains 2056 face images, each with 128 x 128 pixels. The dataset includes faces of different races (mainly white and black), postures, and lighting conditions, and the facial images are mainly images of middle-aged and young women. Moreover, the background of the facial image is single, and the facial posture is relatively uniform (all positive facial images), which can be well applied to facial appearance evaluation problems. However, this dataset has a small amount of data and has certain limitations when linking with makeup skills. This is reason why we further collected photos from the makeup videos of 18 makeup skills on the Internet.

2.2 System Structure

Facial beauty improvement aims to classify (such as high/average/low) or regress facial features in images with different makeup skills, and give accurate recommendations to obtain a better facial beauty score [37-40]. In the regression problem, it can be divided into absolute value regression (i.e. inputting a single image and outputting the corresponding face value score) and relative value regression (i.e. inputting paired images and outputting the difference in face value scores) [41-45]. Differing from traditional methods, we improve the existing deep learning system for facial face value evaluation with fuzzy reasoning by the probability matrices and probabilistic semantic trust decision matrices. The overall structure diagram is shown in Fig. 1.

The system admits a meta-learning process, which is also known as learning to learn. Such process is one of the commonly used methods. It can be employed to solve few-shot learning problems in facial beauty improvement by using previous knowledge and experiences to guide the learning of new tasks and enable the network to learn to learn. Meta-learning first trains a better hyperparameter through the considered makeup tasks, and then trains specific tasks with the residual network (ResNet). Consequently, this system can be understood as an extension of the deep residual learning system.

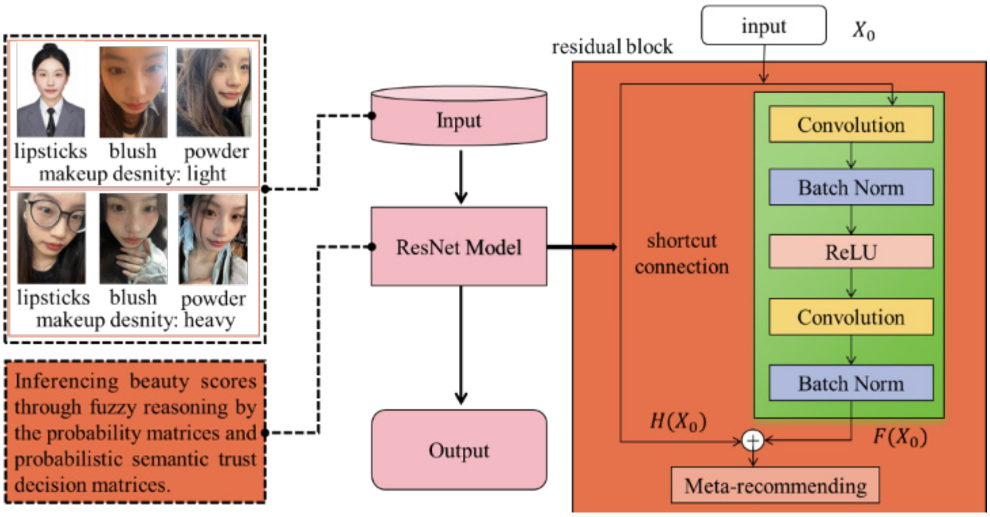

Fig. 1. Structure of the learning system

2.3 Deep Residual Learning

The core idea of deep residual learning is to introduce residual connections (also known as skip connections). As deep residual networks, such learning system can be abbreviated as ResNet [46-51]. Currently, the famous ResNets include ResNet-18, ResNet-50 and ResNeXt-50. The residual connections allow gradients to directly propagate back to earlier layers, thus solving the problem of gradient vanishing in deep networks. ResNet-18 has a total of 18 layers of network, belonging to the shallower ResNet version. The core structure is the basic residual block, which is composed of two 3 * 3 convolutional layers. ResNet-50 has a total of 50 layers, belonging to the deeper ResNet version. Its core structure is bottlenecked residual blocks, consisting of a 1 * 1 convolution layer, a 3 * 3 convolution layer, and another 1 * 1 convolution layer. ResNeXt-50 combines the ideas of VGG and Inception on the basis of ResNet, and increases the network width rather than depth through group convolution, thereby improving performance. It introduces "cardinality" as a new dimension of network width, which is the number of residual blocks in repeated residual block groups. The core structure of ResNeXt-50 is 32 3x3 convolutional kernels and the number of packets is 32. Each kernel has its own input channels, as shown in Fig. 2.

stage	output	ResNet-18	ResNet-50	ResNeXt-50(32x4d)
convl	112×112	7×7, 64, stride 2		
conv2	56×56	3×3 max pool, stride 2		
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times 2$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times 3$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128, C=32 \\ 1\times1, 256 \end{bmatrix}\times 3$
conv3	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times 2$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times 4$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256, C=32 \\ 1\times1, 512 \end{bmatrix}\times 4$
conv4	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times 2$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times 6$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512, C=32 \\ 1\times1, 1024 \end{bmatrix}\times 6$
conv5	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times 2$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times 3$	$\begin{bmatrix} 1\times1, 1024 \\ 3\times3, 1024, C=32 \\ 1\times1, 2048 \end{bmatrix}\times 3$
	1×1	global average pool,1000-d fc, softmax		

Fig. 2. Deep residual learning technologies: from ResNet-18 to ResNeXt-50

We chose ResNet-50 as the backbone of our learning system and will compare its performance with ResNet-18 and ResNeXt-50 at the end of Section 3. That is, the first residual block consists of three residual units, each of which consists of three convolutional layers. The convolutional kernel size of each convolutional layer is 1x1, 3x3, 1x1, and the number of channels is 64,64256. Down-sampling is performed in the second layer 3x3 convolution of the first residual unit, and down-sampling is also performed in other residual blocks at this stage. The second residual block has 4 residual units, and the number of convolutional channels in each residual unit is 128128512. The third residual block has 6 residual units, and the number of convolutional channels in each residual unit is 256256104. The fourth residual block has three residual units, each with a convolutional layer channel count of 512512 and 2048. Note that when connecting the previous residual block to the next residual block, it is necessary to use a 1x1 convolutional layer with side = 2 for identity jump connections. We not only predict the facial beauty score, but also improve it through a fuzzy computation. Recommendations of makeup methods are given according to the fuzzy reasoning results. After the outputs of ResNet-50, the complete probabilistic semantic trust matrix between experts is calculated. The trust transfer relationship between experts is established with a social network group decision model. The decision of recommendations based on probabilistic semantic trust to select the best four makeup methods $\{x_1, x_2, x_3, x_4\}$, and rely on three makeup experts $\{e_1, e_2, e_3\}$, to evaluate these methods.

2.4 Beauty Score Calculation

The residual errors are directly passed to the subsequent layers through shortcut to ensure the integrity of the information and simplify the goal and difficulty of learning. The number of channels at the two ends of the Shortcut Connection connected by the solid line is different, so the calculation method used is:

$$y = F(x) + Wx. \tag{1}$$

where x is the input data and W is a convolution operation, used to adjust the channel dimension of x.

As stated in Section 2.1 and Section 2.3, we improve ResNet-50 for facial face value evaluation with fuzzy reasoning through a series of matrices. These matrices are the probability matrices and probabilistic semantic trust decision matrices, where fuzzy sets are used to express the concept of ambiguity.

In these fuzzy sets, the degree of membership refers to the degree of membership of the set elements to the set, expressed by μ. We used membership function to describe the fuzzy set usually expressed by μ_A.

The makeup methods (abbreviated as *tm*) are defined as

$$T = \{tm_1 + tm_2 + ... + tm_n\}. \tag{2}$$

The corresponding beauty scores (abbreviated as *tbs*) are defined as

$$S = \{tbs_1 + tbs_2 + ... + tbs_m\}. \tag{3}$$

Assuming that the values of k makeup methods are $\mu_1, \mu_2, ..., \mu_k$. Then we can calculate the value range of the beauty score of their combined makeup method from

$$\overline{\mu} = \frac{\sum_i^k tbs_i \mu_i}{k}. \tag{4}$$

2.5 Learn to Learn Makeup Skills

The steps of learning to learn makeup skills are as follows:

(1) Initialize the relevant parameters and quick connection of residual blocks;

(2) The initial beauty score is calculated and the influences of each makeup method are evaluated with ResNet-50, where the improvement of beauty scores of these methods are defined as Equation (5).

$$\Delta y = \Delta F(x) + W\Delta x. \tag{5}$$

where Δy represents the improved beauty score, Δx represents the variation in the input data.

(3) Calculate the beauty scores associated with different makeup skills;

(4) Find an optimal combination of makeup methods by fuzzy reasoning;

(5) Repeat steps (2)-(4) to generate the best recommendations of current makeup methods.

3 Experimental Results and Analyses

3.1 Quickly Connected System

Results from the first step is shown in Fig. 3. In various quick connections of the residual blocks, only when the original method is adopted is the error rate minimized to 6.6%. All other methods result in a higher error rate. In Fig. 3(b), the features are scaled according to a constant value, leading to an error rate of 12.4%. Fig. 3(c) introduces an additional convolutional branch for dimensionality reduction. The processed features, after passing through a sigmoid function, are combined with both the skip-connection branch and the main branch, resulting in an error rate of 8.7%. Fig. 3(d) adds a convolutional branch for dimensionality reduction, but the processed results are combined only with the main branch, leaving the skip-connection branch unaffected; this leads to an error rate of 12.9%. Fig. 3(e) directly applies dimensionality reduction to the main branch, resulting in an error rate of 12.2%. In Fig. 3(f), dropout is applied to the main branch features, yielding the worst performance with an error rate exceeding 20%.

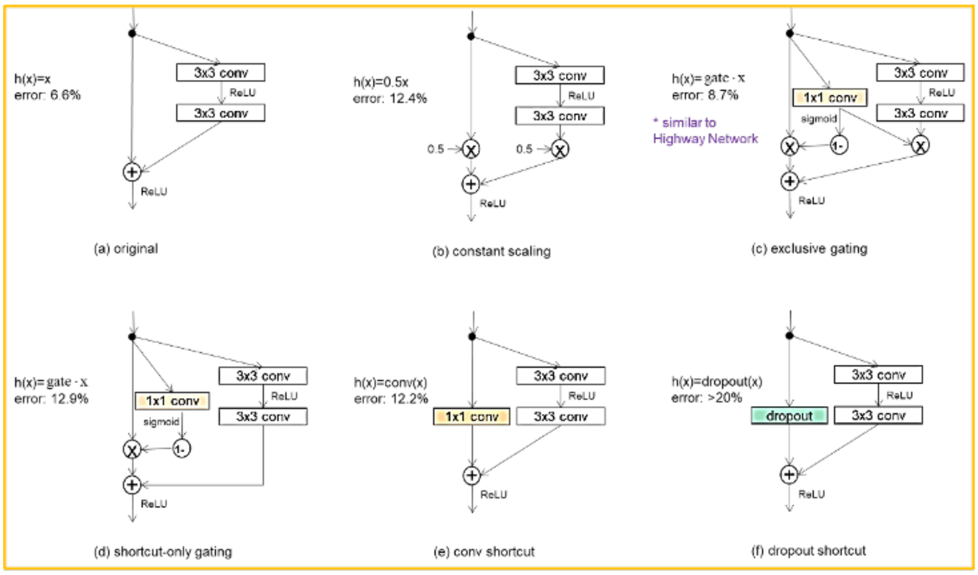

Fig. 3. Quick connection in our learning system

Facial beauty evaluation aims to classify (such as high/average/low) or regress facial features in images to obtain specific facial score. In the face value regression problem, it can be divided into absolute value regression (i.e. inputting a single image and outputting the corresponding face value score) and relative value regression (i.e. inputting paired images and outputting the difference in face value scores). Both traditional methods and deep learning methods met a problem of gradient vanishing or exploding when the number of model layers increases. In traditional neural networks, especially in image processing, a lot of convolutional layers, pooling layers, etc. are used, and each layer extracts features from the previous layer. The number of layers increases, degradation and other issues generally occur. Quick connection in our learning system can solve this problem.

3.2 The Improved Facial Beauty

The improved beauty is shown in Fig. 4. The model achieved the highest score on light powder testing, reaching 88.44, while the lowest score was achieved on light lipstick, at 70.9. The probability scores for each level were different across the various test samples. In particular, for light powder and heavy lipstick, the samples were most likely classified as beautiful, indicating good color, shine, evenness, and delicacy in makeup application. In the case of heavy powder, the probability of samples being classified as little was nearly half. For the remaining aspects, the highest probability of samples was general, indicating that people have average makeup skills in these areas.

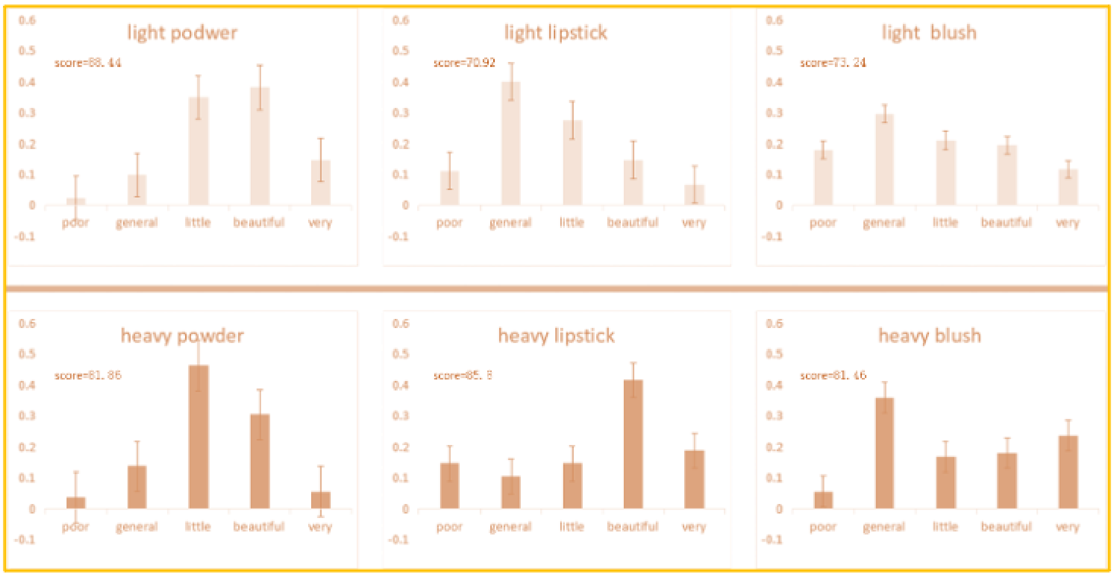

Fig. 4. The improved facial beauty

In this learning processes, a centralized transformation of input data (subtracting the mean from the data) is carried out to accelerate the learning speed of the system. Because of errors between the predicted beauty score of ResNet-50 and the actual beauty score, we also trained the errors of the learning system to correct residuals for more accurate results. We calculated the improved beauty score from Equation (6) as follows.

$$\Delta S = S - S_{\text{initial}} + \varepsilon. \tag{6}$$

where S_{initial} is the initial facial beauty score predicted result of ResNet-50, S is the facial beauty score after an improvement with makeup methods and ε is the errors of the learning system to further correct residuals.

3.3 The Improved Facial Beauty

Scores from fuzzy computation is shown in Fig. 5. As stated in Section 2, we collected enough experimental photos from the internet, which used three makeup methods: powder, lipstick, and brush, and two makeup concentrations: light and heavy, totaling six combinations. For each experimental photo of each combination, the appearance score is given, and the obtained scores are divided into 5 beauty levels based on their level of beauty: poor, general, little, beautiful, and very. The corresponding scoring frequency for each beauty level is calculated, and the average score is recorded as the final appearance score. But it is worthy to point out that the image data on the internet is easily affected by background noise, and it is difficult for the same subject to collect all the desired makeup methods. Hence, we also selected a volunteer to apply makeup according to the specified method, in order to eliminate the impact of differences between different subjects.

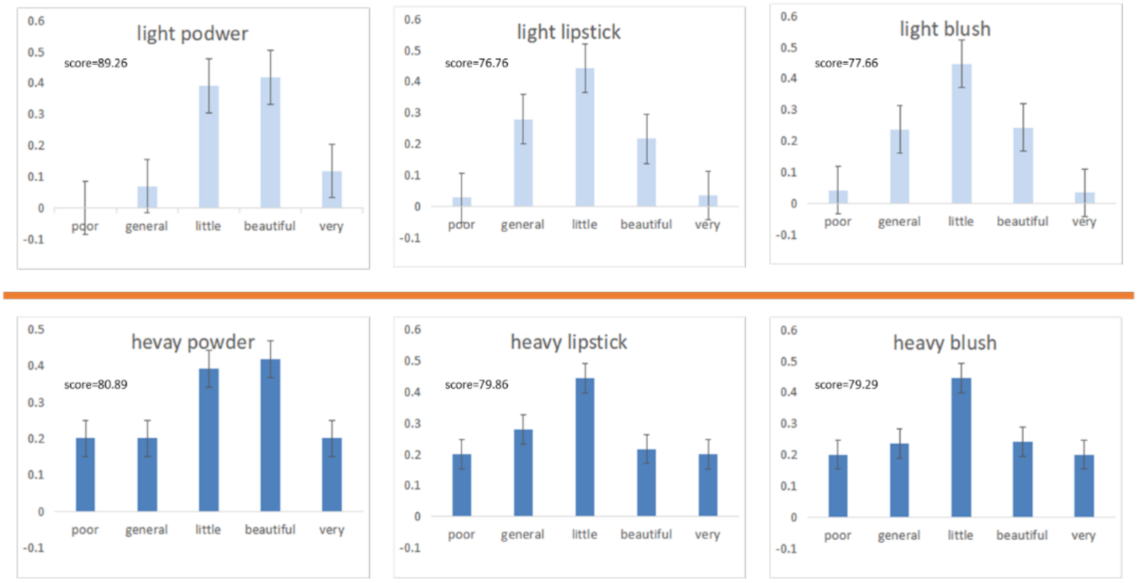

Fig. 5. Scores from fuzzy computation

Experimental results with the data of this volunteer are from a fuzzy computation, where the max-min fuzzy reasoning strategy was performed. The scores of the different sample data of the volunteer in the model show a large difference, with a gap of 12.56 between the highest score in light powder and the lowest score in light lipstick. Among them, the label grade distribution of light and heavy samples is relatively similar. Except for powder being classified as beautiful with the highest probability, the highest probability of other sample grades is little, indicating that the volunteer's makeup skills are relatively ordinary.

3.4 Recommended Makeup Methods

Recommended makeup methods are shown in Fig. 6. Experimental results of the learning system with the data collected from different makeup skills are respectively shown. The model's performance remains optimal for light powder and worst for heavy lipstick, even with two different makeup techniques. Among the tested samples, the probability distribution of the classification levels in the model is similar for the different makeup techniques. Except for powder being the most likely to be classified as beautiful and the least likely to be classified as poor, little is the most likely classification level for the remaining samples. Therefore, powder is the least error-prone part of makeup under different techniques.

In Fig. 6, the decision models are based on probabilistic semantic trust to select the best four makeup methods $\{x_1, x_2, x_3, x_4\}$, and rely on three makeup experts $\{e_1, e_2, e_3,\}$ to evaluate these methods. In Sections 3.1 and 3.2, each makeup method is used separately, while in real life scenarios, various makeup methods should exist in combination. Therefore, we have listed four makeup combinations, each consisting of three makeup methods. That is, x1 is a combination of light powder, light lipstick, and heavy blur. The combination x2 consists of heavy powder, heavy lipstick, and heavy blur. The combination x3 consists of heavy powder, light lipstick, and light blur. The combination x4 consists of light powder, heavy lipstick, and light blur. The values of these four combinations can be used to sum up the beauty scores after makeup. Recommended makeup methods are naturally generated from a calculation of the scores of the four makeup combinations in sequence and compare them.

Fig. 6. Recommended makeup methods

3.5 Comparison with Existing Systems

A comparison with existing algorithms (ResNet-18 and ResNeXt-50) is shown in Table 1. In the ResNeXt-50 network, the number of residual units contained in each residual block is the same as ResNet-50, with two differences: firstly, the number of channels in the convolutional layer of each residual unit in ResNeXt-50 is twice that of ResNet-50; The second point is that all 3x3 convolutional layers, corresponding channels, will be divided into 32 groups to reduce the number of parameters. For example, in the first residual block, the 128 channels of the 3x3 convolutional layer of each residual unit will be divided into 32 groups, each with 4 channels, which means there are 32 sets of 1x1128 to 3x3,4, and then 1x1256 convolution operations, and these 32 sets of channels will be concatenated. The number of parameters has been reduced from 3x3x128x128=147456 to 3x3x4x4x32 = 4068. Grouping convolution enables the model to learn richer feature representations, while also effectively controlling the amount of computation and parameter count. The network structure of ResNet-18 is much more simplifier than ResNeXt-50. In Conv1, the input image is first processed with a 7x7 convolutional kernel of 64 channels with side = 2, and the output feature size is 112x112. In Conv2, the feature is maximally pooled with a 3x3 maximum of side = 2, and then enters the first residual block. This residual block includes 2 residual units, each residual unit includes 2 convolutional layers, each convolutional layer is composed of a 3x3 convolutional kernel of 64 channels, and the output feature size is 56x56. In Conv3, the feature enters the second residual block, which also includes two residual units. Each residual unit consists of two 3x3 convolutional layers with

128 channels, and the first convolutional layer of the first residual unit is down-sampled using stream = 2. Conv3 outputs a feature size of 28x28. In Conv4, the feature enters the third residual block, which has 256 convolutional channels. The first convolutional layer also undergoes a down-sampling, and Conv4 outputs a feature size of 14x14. In Conv5, the feature enters the fourth residual block, which has 512 convolutional channels. The first convolutional layer also undergoes a down-sampling, and Conv5 outputs a feature size of 7x7. It should be noted that in each of the four residual blocks, there are Batch Normalization and ReLU activation after each layer of the volume. Finally, the predicted classification results are obtained by applying the global average pooling layer and SoftMax to the features.

Table 1. Comparison with existing systems

System	MAE	RSME	Time (minutes)	Time*MAE	Time*RMSE	The overall cost
ResNet-18	0.2518	0.2713	49.7	12.51	13.48	25.99
ResNeXt-50	0.2018	0.2335	252.5	50.95	58.96	109.91
Our system	0.2129	0.2417	52.4	11.16	12.67	23.83

The best performance is red-highlighted in Table 1. The MAE and RSME values of ResNeXt-50 are 0.2018 and 0.2335, respectively, implying that ResNeXt-50 is the most accurate system. But it costs much more time than the other two systems. The time cost of ResNet-18 is 49.7 minutes, which is the least among these three ones. But its MAE and RSME values are bigger than the other two systems. Our system is more accurate than ResNet-18 and the training time is much less than ResNeXt-50 in analyzing the users' facial features. The Time*MAE and Time*RMSE values of our system are also the smallest. The overall cost is only 23.83, even less than ResNet-18. Therefore, it is most suitable among these three systems for further constructing a deep learning system for accurate and real-time makeup recommendations.

4 Conclusion

This paper introduces an algorithmic methodology for facial beauty assessment and personalized makeup recommendations, leveraging both deep learning and fuzzy logic reasoning. The proposed method facilitates real-time evaluation of facial aesthetics and, based on these evaluations, delivers tailored makeup advice to users. Additionally, we incorporated a group decision-making model underpinned by probabilistic linguistic information from social networks, offering a fresh perspective for the selection of makeup techniques. The key contributions of this study are as follows:

(1) A facial beauty assessment system through deep learning was developed. We integrated the ResNet-50 deep residual network model and subjected it to thorough training and validation phases to predict facial aesthetics. To enhance the accuracy of our predictions, we further correct the model's prediction residuals.

(2) We developed a fuzzy logic reasoning model designed to offer personalized makeup recommendations. Building on the foundation of the beauty score assessment, we further explored the potential effects of various makeup techniques on facial aesthetics. Through fuzzy logic reasoning, we provided users with specific beauty scores and makeup suggestions for four characteristic makeup combinations.

(3) A group decision-making model in social networks that leverages trust relationships and incorporates probabilistic linguistic information was implemented. This model considers user interactions and feedback on social networks, as well as prevailing trends in makeup brands and styles. Integrating these insights, the model furnishes a more comprehensive and nuanced perspective for makeup recommendations. Moreover, we investigated the associations between different parameters and makeup suggestions, ensuring the provided advice remains both scientifically robust and pragmatically applicable.

Some issues in the paper also remain to be further discussed.

(1) Although the proposed system for facial beauty evaluation can help us better understand the influencing factors of beauty score, we are still limited by the size of the dataset and the limitations of the volunteers' makeup skills. This makes it difficult to meet the demand for accurate recommendations for the users. To further improve the robustness of the system for practical users, the subsequent researchers are encouraged to shift towards large-scale data collection on plenty of volunteers with good makeup skills.

(2) Improvement of the deep residual learning models. Deep residual learning models have been widely applied in multiple computer vision fields, such as object detection, image classification, image segmentation, face

recognition, etc., and their performance often exceeds traditional methods. But the early datasets of makeup skills are always small in scale and insufficient to address the issue of facial beauty evaluation. As the backbone of a real-time system for recommending makeup skills, there is still a big space for further improvement.

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