Rule-Based Facial Makeup Recommendation System

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Abstract— **Makeup style plays a key role in the facial appearance making it more beautiful and attractive. Choosing the best makeup style for a certain face to fit a certain occasion is a full art. Also, foretelling how the face will look like after applying the proposed makeup style requires a high imagination. To solve this problem computationally, an automatic and smart facial makeup recommendation and synthesis system is proposed in this paper. This system starts by classifying the makeup related facial traits that makeup artists consider to decide the makeup style; Then, a rule-based makeup recommendation system is built by creating a knowledge base that models the relation between the *facial style attributes* and *makeup style attributes*, taking into account the occasion such as daily makeup or heavy makeup and the desired trend with semantic text explaining logic behind the recommended style. Finally, we developed an automatic facial makeup synthesis system to apply the recommended style on the facial image as well. To this end, a new database with 961 different females photos collected and labeled. To evaluate the performance of the proposed system, an extensive experimental analysis is conducted on the automatic facial attributes classification, the recommendation efficiency and the synthesis accuracy under different conditions. The obtained results show the effectiveness and flexibility of our proposed fully automatic framework.**

I. INTRODUCTION

Facial makeup plays an important rule in the outer look of the person. Several studies showed that applying facial makeup which increases the visual attractiveness [1], gives younger look and keep the person look following the current trends has positive effects on the person self-esteem, others assessment of the person's skills [2].

Choosing a certain makeup style to fit a certain facial traits for specific occasion can be a challenging question that many people face it frequently. Even though after deciding which makeup style to wear, it is still difficult to foretell how the face will look like after applying that style in reality.

Rule-based recommendation systems showed an efficient performance in different domains such as in human emotion detection [13], online discussion forums [14], stock market prediction [15]. More complete survey a bout recommendation systems can be found here [16]. This success of this systems motivated us to use rules for facial makeup recommendation for main two reasons: 1) the ability of modeling human knowledge about makeup art as a knowledge base and using inference engines to inquire this knowledge base to have the recommendation results later; 2) the flexibility of such recommendation system to be updated by new trends and able to recommend different styles for the same person.

In this paper, we aim to propose a fully automatic facial makeup recommendation and support framework. Main contributions of this work can be summarized by: 1) a new dataset contains 961 females (before and after makeup) from different ethnic groups with manual labeling; 2) fully automatic and flexible rule-based recommendation and support system for facial makeup that covers different trends accompanied with a textual analysis for the logic behind the recommendation; 3) an automatic makeup synthesis process that addresses each element of the makeup style separately.

II. MAKEUP RECOMMENDATION SYSTEM

In this work, we proposed a fully automatic makeup recommendation and synthesis system that consists of three main phases: 1) facial attribute automatic classification, 2) Rule-based makeup recommendation system and 3) automatic makeup synthesis process. The details of each part are discussed bellow. First, we start by presenting our before-after makeup dataset oriented for makeup recommendation.

A. Before-After Facial Makeup Dataset

Facial makeup analysis and recommendation is still a new research direction in computer vision, multimedia and machine learning fields. The few previous works are based either on small datasets or not well annotated ones like [17], [7]. The lack of public and well annotated datasets for makeup recommendation motivated us to collect a new dataset for this purpose. In our dataset, 961 females with before and after makeup pairs of photos are collected. All photos are in good quality, frontal pose with no occlusion by hand or hair. They are spanned over four ethnic groups (African, Asian, Caucasian and Hispanic).

For better usability of this dataset, three trained students are hired to label all images before makeup to define the facial attributes and after makeup to define the makeup style attributes. For more reliable labeling, every student labeled all the images separately and majority voting is considered in the case of conflict. The important facial attributes from the viewpoint of makeup experts are categorized into main classes and labeled manually as shown in Table.I. For after makeup labeling, every makeup style consists of three main parts that are related to skin, eyes and lips basically and it can be described precisely by knowing the class value of each attribute. Table.II summarizes the twelve elements of the makeup style considered in our system.

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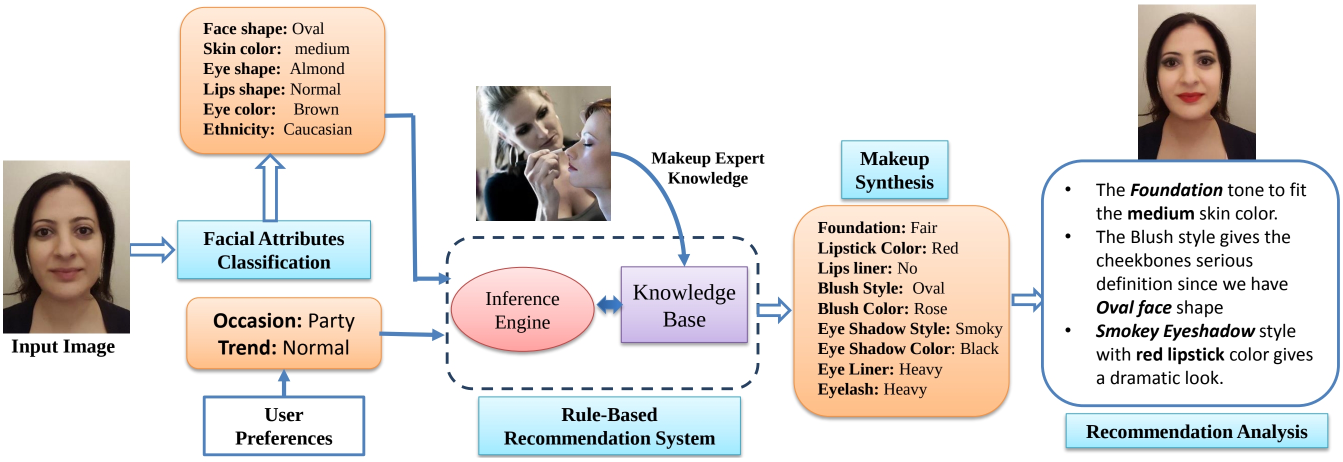

Fig. 1. Overall overview of the proposed system. It starts by facial attributes classification. These attributes are passed along with user preferences to the Rule-based makeup recommendation. The recommendation system suggests makeup style attributes values using the inference engine. The suggested makeup style is synthesized on the facial image. The logic behind our recommendation is demonstrated as a text automatically

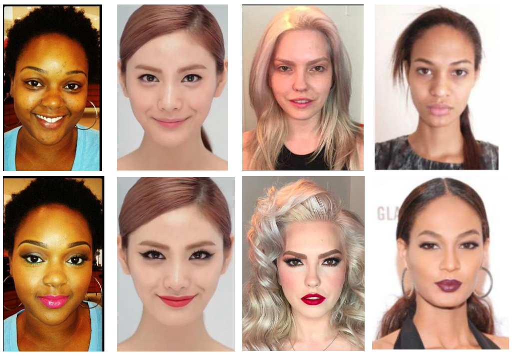

Fig. 2. Four females from our collected *Before-After* makeup database belong to four different ethnic groups

TABLE I

CLASSES OF FACIAL ATTRIBUTES

Face Attribute	Classes
Skin color	Light; Fair; Medium; Dark
Face shape	Oval; Square; Round
Eye shape	Monolid; Upturned; Downturned; Hooded; Round; Almond
Lips shape	Thin; Normal; Thick
Eye color	Green; Hazel; Blue; Brown; Black
Ethnicity Group	African; Asian; Caucasian; Hispanic

From Table.II, we can see that the foundation color follows the skin color classes. The blush style follows the face shape, where we considered three blush styles that fit the three face shape that we have. Intensity of foundation and blush can be light for every day makeup or heavy for heavy makeups.

B. Facial Attributes Classification

Since our system follows the concept of suggesting makeup style that fits certain facial attributes, the ability to classify these attributes from before-makeup photos is an important step. To this end, face++ framework [18] is used to detect 83 facial landmarks in facial image and different regions of interest are extracted that correspond to different facial attributes according to their relative positions to certain landmarks as illustrated in Figure.3. Face shape,

TABLE II

CLASSES OF MAKEUP STYLE ATTRIBUTES

Makeup Attribute	Classes
Foundation color	Light; Fair; Medium; Dark
Foundation intensity	Light; Heavy
Blush style	Oval; Square; Round
Blush color	Blanc; Pink; Plum; Beige; Bronze; Coral; Copper; Orange
Blush intensity	Light; Heavy
Lipstick color	Pink; Red; Orange; Purple; Nude
Lip liner	Yes; No
Eyeshadow style	Cut Crease; Gradient; Smoky, Cat Eye; Halo Eye; Natural eye
Eyeshadow color	Brown; Cream ; Blue; Warm; Smoky
Eye liner	Light; Heavy; Winged
Eye lash	Light; Heavy
Eye brows	Black; Brown; Blond

Skin color and Ethnicity classification are done using facial region called R_1; R_2 region is used for eye shape while R_3 is used for eye color. Lips shape processed via R_4. The best feature vector to each attribute is obtained form the designated region via a combination of three shape and color features which are: RGB-Histograms, HOG [19] and LBP [20]. The combination is selected empirically to extract the best feature vector for each attribute. Multi-class SVM classification model using LIBSVM [21] is adopted for training and classification after dimensionality reduction of the extracted feature vector using PCA [22].

C. Rule-Based Makeup Recommendation System

Make recommendation is a challenging problem in both multimedia and machine learning. The few works appeared recently to address this problem are surveyed briefly here. In [7], beauty e-Expert suggestion system for makeup and hair style was presented using generative recommendation model. A localized deep learning framework was proposed in [8] with similarity based recommendation step. The similarity is measured via Euclidean distance between L-2 normalized deep facial features proposed in [9]. In [10], rules and examples are used jointly to learn deep neural network for makeup recommendation. Rule-based makeup recommendation is presented in [11], but this work considers only the skin color and gender to recommend a makeup style out limited number of styles available in the dataset and can't handle different makeup trends for different occasions or events.

Given a facial image without makeup, after the facial attributes automatic classification listed in Table.I, the person face image before makeup is coded as $F \in \mathcal{F}$ where $\mathcal{F}$ is the total group of facial images before makeup. Also, $F = \{f_i\}_{i=1}^{N}$ where f_i is the i-th facial attribute value and N is the total number of facial attributes. Makeup styles is also denoted as: $\mathcal{M} \ni M = \{m_i\}_{i=1}^{D}$ where M is a makeup style and m_i is the i-th makeup style attribute value as given in Table.II and D is the total number of makeup attributes. A knowledge base that model the experience of makeup experts is designed by interviewing makeup experts and reviewing makeup tutorials as *if-then* rule statements where the antecedent or premise in the *if*-part is one or more facial attribute or makeup attribute values and the *occasion* and the consequent in the *then*-part is one of the makeup attributes value basically. Since the makeup to wear for the same person can change significantly according to the occasion, we developed six different styles namely: *Daily:* it is a light makeup for daily use for work or school; *Professional:* it is for serious events such as date or party; *Smoky:* it is a makeup style has been promoted basically by Kim Kardashian with smoky eyes and nude lipstick color; *Asian:* it comes with winged eyeliner and red or pink lipstick; *Disco* style includes colorful and heavy eye shadows with hot lipstick colors; *Gothic* style has a very dark lipstick colors such as black and dark red and blue with heavy black eye shadows. This flexibility in recommendation is embedded in our knowledge base and makes our recommendation system richer and easier to keep it up to date by comparison to state of the art makeup recommendation frameworks. Here we list a sample of three rules from our 50 rules size knowledge base.

- **Rule 1:** If (*Occasion= daily* and *Skin Color= Medium*) then (*foundation color= Medium* and *foundation Intensity= light*)
- **Rule 2:** If (*Occasion= professional* and *Skin Color= Medium*) then (*foundation color= Medium* and *foundation Intensity= Heavy*)
- **Rule 3:** If (*Skin Color= light* and (*Lips shape= thin*) then (*lipstick color= (Pink, Red)* and *Lip liner= Yes*)

We can see from Rules 1 and 2 how the difference in the foundation intensity attribute changes under same facial attributes but in different occasions. In Rule 3, we can see that we may have more than one available suggestion for the same makeup attribute under the same facial attributes. To solve this conflict and make our knowledge base more smooth, we exploited the available annotation of after makeup images in our collected database and we selected the choice that had higher frequency under the same premises which are the skin color is light and the lips shape is thin in this rule. Here we exploit the available knowledge from the database.

To make the system friendly with users, a semantic analysis feature is added to describe in text the logic behinds choosing certain makeup element either by its relation to the facial trait or to another makeup element as depicted in Figure.1.

After building the knowledge base by interviewing makeup experts, the *inference engine* is an important part to get knowledge out of the rule by reasoning on the the knowledge base for certain test (query) in forward chaining, backward chaining or both. It does the reasoning process by linking the knowledge base information with the automatically classified facial attributes and the occasion information. The output of the inference engine after the reasoning step is the values of the makeup attributes which will be passed to the makeup synthesis automatic system to be applied on the facial image. We used *Clipsmm* C++ inference library[3] to implement our rule-based makeup recommendation system.

D. Automatic Makeup Style Synthesis

The proposed automatic makeup synthesis for every element consists of two parts: 1) Mask selection to determine at what part of the face this element will be blended; 2) Mask and color blending which determines what color and mask will blended on the facial area.

For mask selection, there are two main methods to decide the right mask for a certain makeup style element. The first one is by defining the mask shape from the detected landmarks on the facial image which fits the facial region shape. This method is adopted for foundation, lipstick and eye brows elements in our framework. The second method is followed for eye shadow, blush, eye lash and eye linear, where there are different masks have been already developed to fit different styles for certain makeup elements as mentioned in the Table.II. After deciding a general template, a Thin-Plate Spline wrapping [23] is applied to blend these predefined masks on the input facial region shape by matching the landmarks on the facial region with predefined corresponding points on the mask for accurate synthesis.

After deciding the mask, the second step is blending the recommended color for that makeup element on the facial photo following the mask settings. This step is implemented using different types of blending approaches for different makeup elements. Soft light blend is used when keeping the contrast between the mask region and the original facial photo, such as in lipstick and foundation elements, is important. Soft light blend is given by:

$$f(x, y) = \begin{cases} 2xy + x^2(1 - 2y) & \text{if } y < 0.5 \\ 2x(1 - y) + \sqrt{x}(2y - 1), & \text{otherwise} \end{cases} \tag{1}$$

where x is the facial photo layer and y is the mask layer. This blending is done for every RGB channel separately.

Alpha blend method is adopted alone in lips-liner and eye lash elements to show the contrast between the region of the mask and the background and it is given by:

$$f(x, y) = alpha \times x + (1 - alpha) \times y \tag{2}$$

[3]www.clipsrules.net

TABLE III

FACIAL ATTRIBUTES CLASSIFICATION: REGION OF INTEREST (ROI), DESCRIPTOR, NUMBER OF CLASSES AND THE ACCURACY (%)

Face att.	ROI	Descriptor	# classes	Acc.
Skin color	R1	RGB-Hist, HOG	4	83.20
Face shape	R1	HOG	3	87.95
Eye Shape	R2	HOG,LBP	6	61.05
Lips Shape	R4	HOG,LBP	3	78.41
Eye Color	R3	RGB-Hist	5	81.00
Ethnicity	R1	RGB-Hist, LBP	4	82.42

The *alpha* value varies between $[0, 1]$. It is decided in an empirical way and by taking into consideration facial attributes values as well.

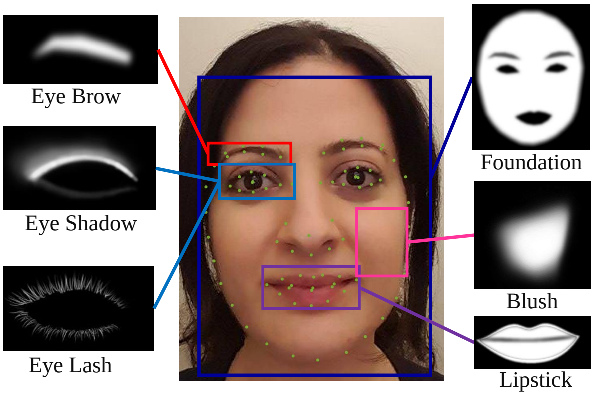

Fig. 3. Facial regions of interest for different facial attributes classification and makeup elements' related masks for add-on

III. EXPERIMENTAL EVALUATION

In this section, we conducted a qualitative and quantitative analysis for the proposed system to evaluate the performance of the three phases of the framework.

A. Facial Attributes Classification

Following the procedure explained in Sect.II-B, we conducted our facial attributes automatic classification using multi-class SVM classifier [24]. This experiment is applied on the 916 before makeup images in the collected dataset. We followed 10-fold cross validation protocol by selecting 90% of the images for training and 10% for testing in every round and repeated that 10 times to cover all images in the testing phase and reporting the average classification accuracy for each trait separately. We used different combinations of RGB-Histogram, LBP and HOG descriptors for each attribute. These combinations are selected empirically. Results are reported in Table.III where it gives the facial attribute, the facial region of interest cropped, descriptors used, the number of classes and the obtained classification accuracy. Good classification rates are obtained for most of the attributes such as 87% for face shape and more than 80% for skin color, eye color and ethnicity. For the eye shape, it is 61.05% where there are 6 different shapes which makes it a challenging task even for people. Also, the *Round* eye shape has a low number of samples in our collected dataset.

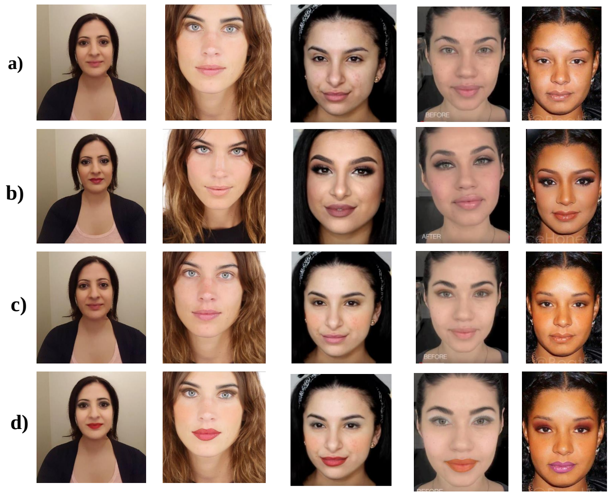

Fig. 4. Five samples used in this experiment. In column a) the facial image before makeup, b) after professional makeup, c) after our suggested daily makeup, d) after our suggested professional makeup

B. Makeup Recommendation Perceptual Evaluation

To evaluate the performance of the proposed rule-based recommendation and synthesis system, two different qualitative experiments are conducted. In the first experiment, 20 images without makeup are randomly selected; the facial attributes are classified and the two recommended makeup styles *daily* and *professional* are applied. A triplet for each of those 20 different females photos consisted of (without makeup, with light makeup, with heavy makeup) are presented to 40 different persons (20 males and 20 females from different countries). The participants have been asked to evaluate each makeup style by giving a score between 1 to 5 as: {1.Very bad, 2.Bad, 3.Fine, 4.Good, 5.Very good}. The average percentage of each evaluation obtained for the daily and the professional makeup styles are reported from females and males separately in Figure.5.

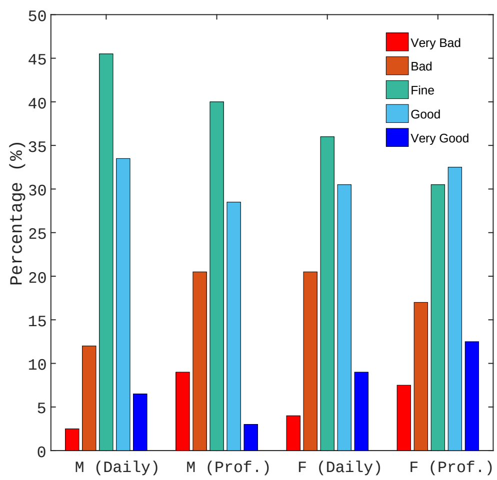

Fig. 5. Perceptual statistical analysis to evaluate our recommendation and synthesis makeup system. where M: denotes to Males, and F. denotes to Females and Prof. is the professional makeup style.

From Fig.5, we can see that males reported fine and good for most of the both styles where very bad and very good

TABLE IV

SUGGESTED MAKEUP VS. THE PROFESSIONAL MAKEUP

	–	-	=	+	++
Male	7%	20%	36%	22%	15%
Female	8%	23%	35%	21%	13%

TABLE V

PROFESSIONAL MAKEUP VS.SUGGESTED MAKEUP

	–	-	=	+	++
Male	17%	25%	31%	22%	5%
Female	15%	23%	33%	22%	7%

are much less. For females, they are more critical in general than males since they pay more attention to details, but they still give fine and good evaluation the highest scores for both daily and professional styles. Also, females give higher percentage for very good score than males in the two styles.

In Fig.4, we can see different samples of the 20 testing images that we used for this experiment. We present the face before makeup, with professional makeup, with our suggested daily and professional makeup styles.

The second experiment to evaluate makeup suggestion is more challenging where the suggested and the professional makeup for 20 females are compared. Makeup images in this survey were anonymized and the participants didnt know which image was from the recommendation system or from the dataset. To do this, pair of photos (suggested makeup and professional one) of 20 females are presented to 40 participants, 20 males and 20 females. The following question has been asked: *Is the makeup at the left is (Much worse(–), Worse(-), Comparable(=), Better(+), Much better (++)) than makeup at the right?*. The position of the suggested and the professional one are exchanged randomly randomly. Following these settings, Two scenarios obtained which are: **Scenario A)** where the suggested makeup is on left. Thus, the question becomes like: *Is the suggested makeup (Much worse (–), Worse(-), Comparable(=), Better(+), Much better(++)) than the professional one?* and the obtained results are presented in Table.IV.

Scenario B), when the professional makeup was on the right, the question becomes *Is the professional makeup (Much worse(–), Worse(-), Comparable(=), Better(+), Much better(++)) than the suggested makeup?*. The statistical results from males and female participants for this scenario are reported in Table.V separately.

From these two tables, it seems that the evaluation comparable in both scenarios has the highest probability, more 30%, and the evaluations Better and Much better together are higher than Worse and Much worse in Scenario A and less in scenario B. These two experiments show the efficiency of the proposed framework from the view point of the end user and the recommended makeup and its synthesis can be close to the real makeup. Since there are other four different trends for facial makeup in the proposed system which are Smoky, Asian, Disco and Gothic, they need to be evaluated as well. In Fig.6, the implementation of the four trends on four females from different ethnic groups is depicted.

To evaluate the quality of the proposed recommendation system for these trends, these four trends are generated for 20 females and are presented to 40 participants (20 males and 20 females). Participants are asked to evaluate each style by a score form 1 to 5 where 1.Very Bad, 2.Bad, 3.Fine, 4.Good, 5.Very good as in the first experiment. The results of this perceptual study are presented in Fig.7. The obtained results show that most of the evaluation lies between Fine and Very good for the four different trends addressed in this experiment.

Fig. 6. Four different makeup trends applied for four different females

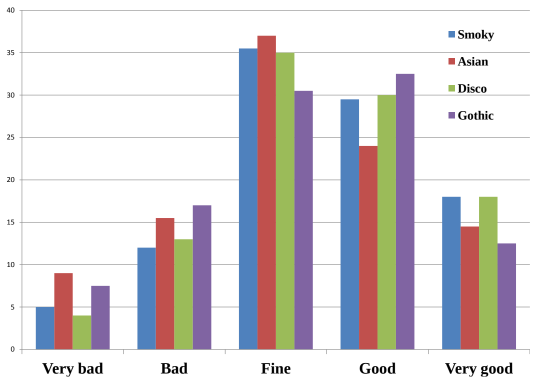

Fig. 7. Four different styles recommendation perceptual evaluation results

C. Makeup Style Synthesis Results

In this section, the aim is to demonstrate the performance of the proposed makeup synthesis implementation for different makeup elements. In this experiment, as illustrated in Figure.8, proposed synthesis results are compared versus two well known manual makeup synthesis websites: *TAAZ*[3] and *DailyMakever*[4]. From Fig.8, it can be concluded that

[3]www.taaz.com

[4]www.dailymakeover.com/virtual-makeover/

TAAZ doesn't support working with eye brows, and the eye lash implementation is far from natural effect. The ability to control the effect intensity is limited in In *Dailymakeover* also and the lips shape detection has accuracy problem. The advantage of using different types of blending and combining two types in some cases for different makeup style elements are the main reason behind obtaining more natural synthesis effect. For example, a natural effect is obtained for foundation and blush elements which requires homogeneous blending with the skin. Also, the eye brows and eye lash effects are elegant where the contrast with the nearby facial area is well preserved. Besides, both of *TAAZ* and *Dailymakeover* require user's intervention while our synthesis is fully automatic one.

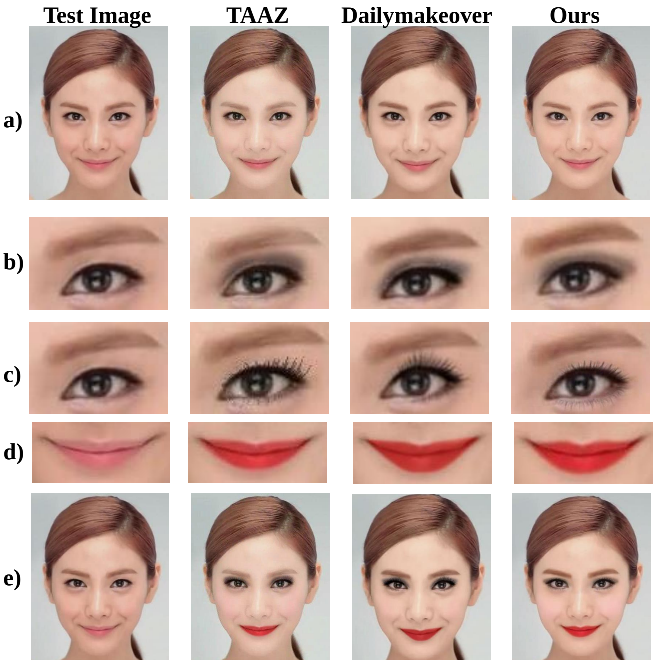

Fig. 8. Comparison of our makeup synthesis results with two main websites. Rows from top to down show a) foundation effect, b) eye shadow and eye brows, c) eye lash, lipstick, 3) blush and overall effect.[Please, see the electronic version for better perception]

IV. Conclusion and Future Work

In this paper, a fully automatic facial makeup recommendation system is proposed. It starts by analyzing the facial traits automatically, then and a rule-based expert system with rich and flexible knowledge base that can make fast and reasonable makeup styles recommendation according to the facial attributes, occasions and certain trend is proposed. The recommended style can be synthesized efficiently on the facial image. The statistical and the perceptual evaluations of the three parts of our recommendation system shows its efficiency and flexibility. Another contribution of this work is *Before-After* makeup dataset which was the baseline of this work. This system can be improved by several aspects which are considered as a future work such as extending the dataset, expanding the system to recommend for females and males, learning the knowledge base rules directly from the labeled data and adding more templates and colors to the makeup synthesis library to recommend more styles.

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