Multi-task Learning of Cascaded CNN for Facial Attribute Classification

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Abstract

Recently, facial attribute classification (FAC) has attracted significant attention in the computer vision community. Great progress has been made along with the availability of challenging FAC datasets. However, conventional FAC methods usually firstly pre-process the input images (i.e., perform face detection and alignment) and then predict facial attributes. These methods ignore the inherent dependencies among these tasks (i.e., face detection, facial landmark localization and FAC). Moreover, some methods using convolutional neural network are trained based on the fixed loss weights without considering the differences between facial attributes. In order to address the above problems, we propose a novel multi-task learning of cascaded convolutional neural network method, termed MCFA, for predicting multiple facial attributes simultaneously. Specifically, the proposed method takes advantage of three cascaded sub-networks (i.e., S_Net, M_Net and L_Net corresponding to the neural networks under different scales) to jointly train multiple tasks in a coarse-to-fine manner, which can achieve end-to-end optimization. Furthermore, the proposed method automatically assigns the loss weight to each facial attribute based on a novel dynamic weighting scheme, thus making the proposed method concentrate on predicting the more difficult facial attributes. Experimental results show that the proposed method outperforms several state-of-the-art FAC methods on the challenging CelebA and LFWA datasets.

I. INTRODUCTION

During the past few years, facial attribute classification (FAC) has attracted increasing attention in computer vision and pattern recognition. The goal of FAC is to predict the attributes of a given facial image, such as attraction, smile and gender, as shown in Fig. 1. FAC has widespread and practical applications, including face verification [1], [2], image search [3] and image retrieval [4]. However, it still remains a challenging task in practice due to the wide variability of facial appearances in viewpoint, illumination, expression, etc.

Recently, most methods of FAC take advantage of convolutional neural network (CNN) for predicting facial attributes, due to the outstanding performance of CNN. Generally speaking, the CNN based FAC methods can be roughly divided into two categories: single-label learning based methods [5], [6], [7], [8] and multi-label learning based methods [9], [10]. The single-label learning based methods first extract the features of facial images via CNN and then use the support vector machine (SVM) for predicting facial attributes individually. In contrast, multi-label learning based methods predict multiple facial attributes simultaneously. For example, Ehrlich et al. [11] propose a novel multi-task restricted boltzmann machine (MT-RBM) method for FAC. Rudd et al. [12] use multi-label learning for FAC by introducing a novel mixed object optimization network (MOON). Zhuang et al. [13] propose a multi-label learning based deep transfer neural network method for FAC, which effectively addresses the problem of facial attributes with unlabelled information. Typically, the above methods usually first pre-process the input images (i.e., perform face detection and alignment) and then predict facial attributes. In other words, these tasks (i.e., face detection, facial landmark localization and FAC) are independently trained, and thus the inherent dependencies among these tasks are ignored. Furthermore, for the loss function in these methods, the loss weights corresponding to different facial attributes are often fixed to be equal. As a result, different facial attributes are equally treated and trained. Therefore, the performance of FAC may not be optimal since the differences between facial attributes are not effectively exploited.

Driven by the above problems, in this paper we propose a novel multi-task learning of cascaded CNN method, termed MCFA, for FAC. Three different but related tasks (i.e., face detection, facial landmark localization and FAC) are simultaneously trained by taking advantage of multi-task learning. Notice that FAC is our target task and the other two tasks (i.e., face detection and facial landmark localization) are the auxiliary tasks. We aim to exploit the inherent dependencies between the target task and auxiliary tasks to improve the performance of FAC. More specifically, the proposed MCFA method jointly trains three cascaded sub-networks (i.e., S_Net, M_Net and L_Net) under three different scales in a unified framework for FAC. The whole framework performs multi-task learning in a coarse-to-fine manner. In addition, a novel dynamic weighting scheme is proposed for automatically assigning the loss weights corresponding to the facial attributes. In this manner, the CNN training stage focuses on classifying the more difficult facial attributes, thus leading to performance improvements.

The major contributions of this paper are summarized as follows:

- We propose a novel and effective method for FAC, which takes advantage of multi-task learning to train three related

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Fig. 1: Exemplars of different facial attributes.

tasks simultaneously. To the best of our knowledge, it is the first work to perform multi-task learning in a unified framework for predicting multiple facial attributes simultaneously. As a result, the performance of FAC can be effectively improved by exploiting the inherent dependencies among different tasks.

• Different from the conventional cascaded method [17] which independently trains each stage, the proposed MCFA method jointly trains different sub-networks in a cascaded manner. Therefore, the proposed MCFA method can achieve end-to-end optimization for better performance.

• Instead of using the fixed loss weights in the loss function, a dynamic weighting scheme, which automatically and dynamically learns the loss weights, is developed by considering the differences between facial attributes. Thus, the proposed MCFA method concentrates on predicting the more difficult facial attributes.

II. THE PROPOSED METHOD

In this section, we describe the proposed MCFA method in detail, which uses multi-task learning of cascaded CNN, for FAC.

A. Overall Framework

The overall framework of the proposed MCFA method for FAC is shown in Fig. 2. In this paper, we explicitly extract multi-scale features in a coarse-to-fine manner to boost the performance of FAC. Specifically, the input image is initially resized to three different scales by average pooling to build an image pyramid, which corresponds to the inputs of the following three cascaded sub-networks.

S_Net: This is the first sub-network, which is a fully convolutional network, called S_Net (Small_Net), in which the input image is resized to 56×56. S_Net is used to extract the coarse features of the input image. For training, we employ multi-task learning to jointly train the sub-network for three related tasks. For testing, we also use the threshold control layers (i.e., the 'Cls score1' layers as shown in Fig. 2) to decide which facial proposals from S_Net contribute to M_Net.

M_Net: This sub-network is similar to the first sub-network, called M_Net (Medium_Net), in which the input image is resized to 112×112. M_Net is used to extract the fine features of the input image. For training, we jointly train the sub-network for multiple related tasks by multi-task learning. For testing, only the passed facial proposals from M_Net, which further rejects many false candidates, are fed to L_Net.

L_Net: This is the third sub-network, called L_Net (Large_Net), in which the input image is resized to 224×224. L_Net is used to extract the subtle features of the input image. For training, the sub-network is learned based on multi-task learning. For testing, only the passed facial proposals are used for performing multiple tasks, where FAC is the target task, while face detection and facial landmark localization are the auxiliary tasks. Therefore, we obtain the final results of FAC from L_Net.

Notice that, different from the method of [17], which uses three cascaded stages of CNN for joint face detection and alignment in a greedy manner (i.e., previous stages are fixed when training the subsequent stages), the proposed cascaded sub-networks are effectively combined in a unified framework. In this manner, we can easily apply the back propagation algorithm to train the whole framework.

Finally, the whole framework combines the losses from the three sub-networks as the final loss.

B. CNN Architecture

As stated previously, the proposed MCFA method consists of three sub-networks: S_Net, M_Net and L_Net. The detailed architectures of these sub-networks are given as follows:
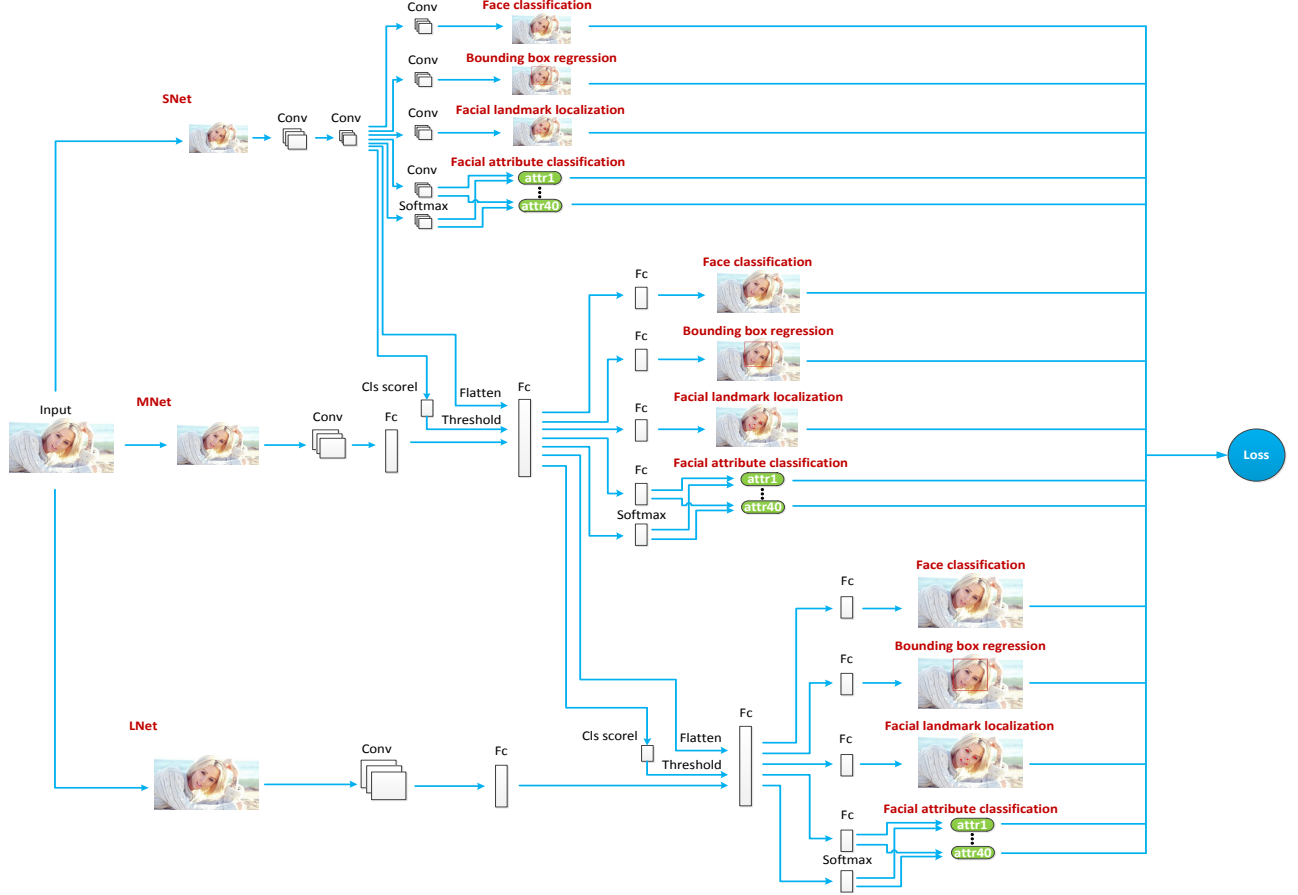
Fig. 2: The overall framework of the proposed MCFA method for FAC. The input image is resized to three different scales (i.e., 56×56, 112×112 and 224×224), which correspond to the inputs of the three cascaded sub-networks (i.e., S_Net, M_Net and L_Net).

S_Net: We use the similar architecture of VGG-16 [16] (from 'conv1_1' to 'conv3_3') for S_Net in the former convolutional layers. The last shared convolutional layer of S_Net is of size $1\times256\times1\times1$.

M_Net: In the former convolutional layers, we use the similar architecture of VGG-16 [16] (from 'conv1_1' to 'conv4_3') for M_Net. Then M_Net outputs a 1024 dimensional fully connected layer, and it concatenates with a 1×256 fully connected layer, which is flattened from the last shared convolutional layer of S_Net. Therefore, the last shared fully connected layer of M_Net is of size 1×1280.

L_Net: Similar to M_Net, we use the architecture of VGG-16 [16] (from 'conv1_1' to 'conv5_3') for L_Net in the former convolutional layers. Then L_Net outputs a 1024 dimensional fully connected layer, which concatenates with a 1×1280 fully connected layer from M_Net.

Note that, after the last shared layer of each sub-network, we use two layers (i.e., two convolutional layers in S_Net and two fully connected layers in M_Net and L_Net) to learn the more discriminative and compact features for obtaining better performance.

C. Training

In the proposed method, we jointly train two auxiliary tasks (face detection and facial landmark localization) for the target task (FAC) by taking advantage of multi-task learning. In this way, the inherent dependencies among these tasks are effectively exploited. Note that, the task of face detection includes two sub-tasks: face classification and bounding box regression.

1) Face classification: Face classification is to perform face/non-face classification for a given image. For each sample x_i, we use the softmax loss:

$$L_i^{cls} = y_i^{cls}log(p_i) + (1 - y_i^{cls})log(1 - p_i), \tag{1}$$

where p_i represents the probability given by the network, which indicates the sample x_i being a face. And $y_i^{cls} \in \{0, 1\}$ is the ground-truth label.

2) Bounding box regression: Bounding box regression aims to predict the coordinates of the facial proposal, which is treated as a regression problem. We employ the Euclidean loss for each sample $\boldsymbol{x}_i$:

$$L_i^{box} = \|\hat{\boldsymbol{y}}_i^{box} - \boldsymbol{y}_i^{box}\|_2^2, \tag{2}$$

where $\hat{\boldsymbol{y}}_i^{box} \in R^4$ represents the coordinate vector (including left, top, height and width) of a regressed facial proposal obtained from the network and $\boldsymbol{y}_i^{box}$ denotes the ground-truth coordinate vector.

3) Facial landmark localization: Similar to bounding box regression, facial landmark localization is also a regression problem. We use the Euclidean loss for each sample $\boldsymbol{x}_i$ as follows:

$$L_i^{landmark} = \|\hat{\boldsymbol{y}}_i^{landmark} - \boldsymbol{y}_i^{landmark}\|_2^2, \tag{3}$$

where $\hat{\boldsymbol{y}}_i^{landmark} \in R^{2k}$ represents the coordinate vector of the facial landmarks (k is the number of facial landmarks and we use 5 facial landmarks, as done in [17]) obtained from the network and $\boldsymbol{y}_i^{landmark}$ denotes the ground-truth coordinate vector.

4) Facial attribute classification: Similar to face classification, we consider FAC as a binary classification problem. The softmax loss with a dynamic weighting scheme for each sample $\boldsymbol{x}_i$ is formulated as:

$$L_i^{attr} = \boldsymbol{\mu}_w^T \cdot \boldsymbol{l}_i^{cls}, \tag{4}$$

where $\boldsymbol{\mu}_w \in R^d$ (see Eq. (6)) denotes the dynamic weight vector corresponding to the d facial attributes and $\boldsymbol{l}_i^{cls} = [l_1^{cls}, l_2^{cls}, \cdots, l_d^{cls}]^T$ represents the softmax loss vector corresponding to the d facial attributes for each sample $\boldsymbol{x}_i$.

5) Joint loss: The joint loss consists of the losses of three cascaded sub-networks (i.e., S_Net, M_Net and L_Net). The joint loss of the proposed MCFA method can be written as:

$$L_{joint} = \sum_{i=1}^{N} \sum_{j=1}^{3} (L_{ij}^{cls} + L_{ij}^{box} + L_{ij}^{landmark} + L_{ij}^{attr}), \tag{5}$$

where N is the number of training examples; j corresponds to the index of three sub-networks. The whole network of the proposed MCFA method can be optimized through the back-propagation algorithm.

6) The dynamic weighting scheme: Inspired by [19], we propose to use a dynamic weighting scheme to automatically assign the loss weights to facial attributes.

We add a layer (i.e., the convolutional layer in S_Net and the fully connected layer in both M_Net and L_Net) and a softmax layer to the last shared features $\boldsymbol{x}$ of each sub-network for learning the dynamic weights. Let $\boldsymbol{\omega}_w \in R^{D \times d}$ and $\boldsymbol{\varepsilon}_w \in R^d$ respectively represent the weight matrix and the bias vector in the convolutional layer or fully connected layer. Then, the output of the softmax layer is

$$\boldsymbol{\mu}_w = softmax(\boldsymbol{\omega}_w^T \boldsymbol{x} + \boldsymbol{\varepsilon}_w), \tag{6}$$

where,

$$softmax(\boldsymbol{\alpha}) = [\frac{e^{\alpha_1}}{\sum\limits_{q=1}^{d} e^{\alpha_q}}, \frac{e^{\alpha_2}}{\sum\limits_{q=1}^{d} e^{\alpha_q}}, \cdots, \frac{e^{\alpha_d}}{\sum\limits_{q=1}^{d} e^{\alpha_q}}]^T, \tag{7}$$

and $\boldsymbol{\mu}_w = [\mu_1, \mu_2, \cdots, \mu_d]^T$ represents the d-dimensional dynamic weight vector with $\mu_1 + \mu_2 + \cdots + \mu_d = 1.0$. $\boldsymbol{\alpha} = [\alpha_1, \alpha_2, \cdots, \alpha_d]^T$ represents a d-dimensional vector. The $softmax$ function converts the d dynamic weights to positive values that sum to 1.0.

According to Eqs. (5) and (6), in order to reduce the joint loss, the more difficult facial attributes will be assigned with larger loss weights. Compared with the conventional methods [6], [11] that use the equal loss weights for all the facial attributes, the proposed dynamic weighting scheme automatically learns the loss weights minimizing the final joint loss. Therefore, the proposed network can focus on the classification of the more difficult attributes by considering the differences between facial attributes.

III. Experiments

In this section, we firstly introduce the two public FAC datasets used for evaluation. Then we discuss the influence of multi-task learning on the final performance. Finally we compare the proposed MCFA method with several state-of-the-art methods.

TABLE I: The detailed settings of the training and testing data on the CelebA and LFWA datasets.

Methods	CelebA		LFWA	
	Training Data	Testing Data	Training Data	Testing Data
MCFA_FLL_FAC	162,770		13,144	
MCFA_FD_FAC	488,310	19,962	19,716	6,571
MCFA_FAC	162,770		6,572	
MCFA	488,310		26,288	

A. Datasets

To evaluate the effectiveness of the proposed MCFA method, we employ two challenging FAC datasets: the CelebA [14] and LFWA [15] datasets. The CelebA dataset is collected in the wild, which contains 202,599 facial images of 10,177 identities, and 40 binary attribute annotations for each facial image. 162,770 images, 19,867 images and 19,962 images are used for training, validation and testing, respectively. The LFWA dataset is another labelled facial attributes dataset in the wild, which has more than 1,680 identities and contains more than 13,000 facial images. The images in this dataset have 73 binary facial attribute annotations.

In this paper, we jointly train three tasks (i.e., face detection, facial landmark localization and FAC). Therefore, we use four different kinds of data annotations for training: 1) Non-faces: we randomly crop several patches, whose Intersection-over-Union (IoU) ratios are less than 0.001 to the ground-truth face, from the CelebA dataset; 2) Faces: we detect the faces from the CelebA or the LFWA dataset; 3) Landmarks: we collect five landmarks of the facial images from the CelebA or the LFWA dataset; 4) Facial attributes: we use the images with labelled facial attributes from the CelebA or LFWA datasets.

B. Influence of multi-task learning

In this subsection, to show the effectiveness of the proposed MCFA method, we evaluate several variants of the proposed MCFA method, which perform multi-task learning by combining different tasks.

Specifically, 'MCFA_FLL_FAC' represents that we jointly train the tasks of facial landmark localization and FAC. 'MCFA_FD_FAC' represents that we jointly train the tasks of face detection and FAC. 'MCFA_FAC' represents that we only train the task of FAC. 'MCFA' represents that we jointly train three related tasks (i.e., face detecion, facial landmark localization and FAC).

The detailed settings of the training and testing data used for different variants of MCFA methods are shown in Table I. The performance obtained by the different variants of the proposed MCFA method on the CelebA dataset is given in Fig. 3.

As shown in Fig. 3, we can see that 'MCFA' achieves better results than the other three variants of the proposed MCFA method (i.e., 'MCFA_FLL_FAC', 'MCFA_FD_FAC' and 'MCFA_FAC'). Therefore, by combining FAC and two auxiliary tasks, the performance of FAC can be effectively improved, which demonstrates the effectiveness of multi-task learning of cascaded CNN. In this manner, the relationship among these tasks is fully exploited.

C. Comparison with state-of-the-art methods

In this subsection, we compare the performance of the proposed MCFA method with several state-of-the-art FAC methods: FaceTracer [20], two versions of PANDA [5] (i.e., PANDA-w and PANDA-l), two versions of LNets+ANet [6] (i.e., LNets+ANet (w/o) (without pre-training) and LNets+ANet), and MT-RBM (PCA) [11]. In Table II, we show the classification accuracy obtained by the proposed MCFA method and the state-of-the-art methods. For the CelebA dataset, we compare the proposed MCFA method with all the competing methods. For the LFWA method, we compare the proposed MCFA method with all the competing methods except for MT-RBM (PCA) [11].

As shown in Table II, the proposed MCFA method significantly outperforms most of the competing methods on the CelebA and LFWA datasets. The other competing methods independently train different tasks in a greedy manner, thus the performance of FAC may not be optimal. In contrast, the proposed MCFA method jointly trains these tasks, which makes use of the inherent dependencies among these tasks. Moreover, the proposed method performs multi-task learning in a coarse-to-fine manner, which extracts the hierarchical features for improving the performance. It is worthy pointing out that the proposed MCFA method considers the differences between facial attributes by using a dynamic weighting scheme. Hence, the improvements for some difficult facial attributes are more obvious (such as the 'Bangs' and 'Wavy Hair' attributes). On the whole, the proposed method achieves superior performance on these two datasets.

IV. CONCLUSION

In this paper, we propose a novel multi-task learning of cascaded CNN method, term MCFA, for FAC. The proposed MCFA method can effectively improve the performance of FAC by exploiting the inherent dependencies between the target task (FAC) and auxiliary tasks (face detection and facial landmark localization). Specifically, MCFA trains three cascaded sub-networks in a unified framework. Moreover, the proposed MCFA method assigns the loss weights to each facial attribute by using a dynamic weighting scheme, which automatically learns the differences between the facial attributes. Experimental results on the CelebA and LFWA datasets show that the proposed MCFA method has achieved significant improvements over several other state-of-the-art methods.
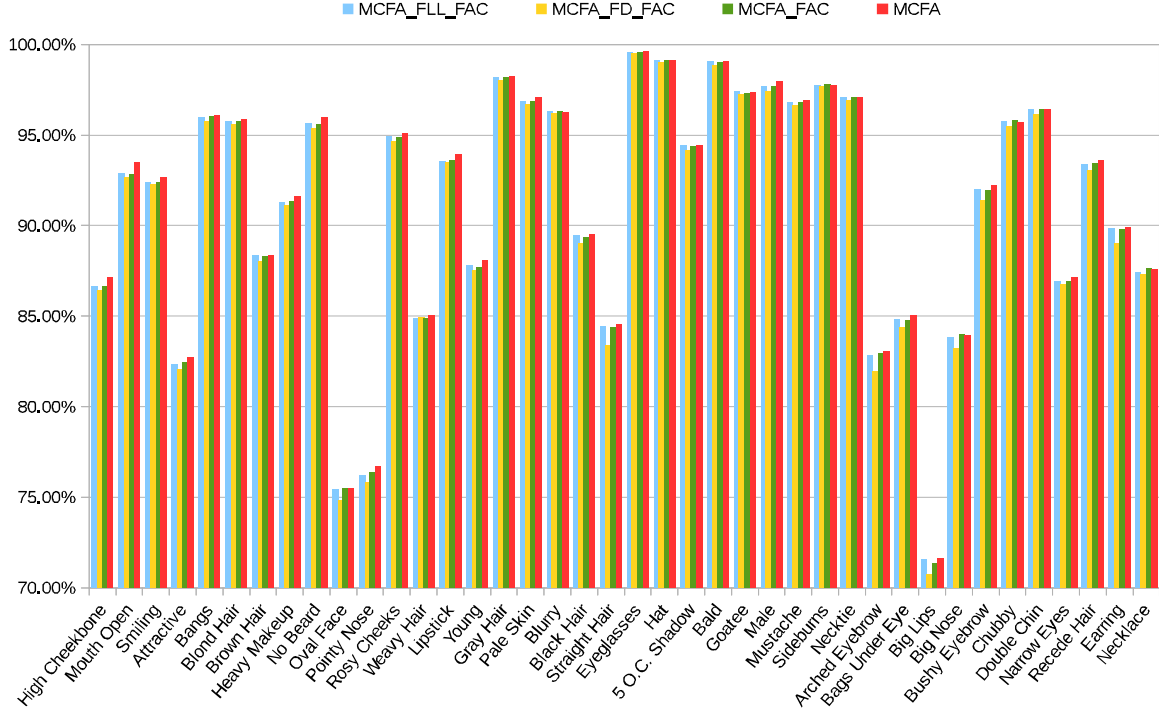
Fig. 3: Performance comparison between different variants of the proposed MCFA method on the CelebA dataset.

TABLE II: The classification accuracy (%) comparison between the proposed MCFA and the state-of-the-art methods on the CelebA and LFWA datasets. The best results are boldfaced.

	Method	High Cheekbone	Mouth Open	Smiling	Attractive	Bangs	Blond Hair	Brown Hair	Heavy Makeup	No Beard	Oval Face	Pointy Nose	Rosy Cheeks	Wavy Hair	Lipstick	Young	Gray Hair	Pale Skin	Blurry	Black Hair	Straight Hair	Eyeglasses
CelebA	FaceTracer [20]	84	87	89	78	88	80	60	85	90	64	68	84	73	89	80	90	83	81	70	63	98
	PANDA-w [5]	80	82	89	77	89	81	69	84	87	62	65	81	76	88	77	88	84	77	74	67	94
	PANDA-l [5]	86	93	92	81	92	93	77	90	93	65	71	87	77	93	84	94	91	86	85	69	98
	ANet [21]	85	85	92	79	94	86	74	87	91	65	67	85	79	91	81	93	89	83	77	70	96
	LNets+ANet(w/0) [6]	84	86	88	77	92	91	78	85	92	63	70	87	75	90	83	93	87	80	84	69	96
	LNets+ANet [6]	**87**	92	92	81	95	95	80	90	95	66	72	90	80	93	87	97	91	84	88	73	99
	MT-RBM (PCA) [11]	83	82	88	76	88	91	83	85	90	73	73	94	72	89	81	97	96	95	76	80	96
	MCFA	**87**	**93**	**93**	**83**	**96**	**96**	**88**	**92**	**96**	**75**	**75**	**95**	**85**	**94**	**88**	**98**	**97**	**96**	**89**	**85**	**100**
LFWA	FaceTracer [20]	77	77	78	71	72	88	62	88	69	66	74	70	62	87	80	78	70	73	76	67	90
	PANDA-w [5]	75	74	77	70	79	87	65	86	63	64	68	64	63	83	76	77	64	70	78	68	84
	PANDA-l [5]	86	78	89	81	84	94	74	93	75	72	76	73	75	93	82	81	**84**	74	87	73	89
	ANet [21]	79	76	82	75	84	90	71	89	69	66	72	71	65	86	79	82	68	75	82	72	88
	LNets+ANet(w/0) [6]	83	78	88	80	84	94	73	91	75	71	76	72	73	92	82	81	81	70	86	71	92
	LNets+ANet [6]	**88**	**82**	**91**	**83**	88	**97**	77	**95**	79	**74**	**80**	78	76	**95**	86	84	**84**	74	90	76	**95**
	MCFA	85	78	88	77	**89**	**97**	77	94	79	**74**	**80**	85	79	94	**87**	88	82	**86**	**91**	77	91

	Method	Hat	5 O.C. Shadow	Bald	Goatee	Male	Mustache	Sideburns	Necktie	Arched Eyebrow	Bags Under Eye	Big Lips	Big Nose	Bushy Eyebrow	Chubby	Double Chin	Narrow Eyes	Recede Hair	Earring	Necklace	Average
CelebA	FaceTracer [20]	89	85	89	93	91	91	86	86	76	76	64	74	80	86	82	76	73	68		81
	PANDA-w [5]	91	82	92	86	93	83	90	88	73	71	61	70	76	82	85	79	82	72	67	79
	PANDA-l [5]	96	88	96	93	97	93	93	91	78	79	67	75	86	86	88	84	85	78	67	85
	ANet [21]	93	86	92	92	95	87	94	90	75	77	63	74	80	86	90	83	84	77	70	83
	LNets+ANet(w/0) [6]	96	88	95	92	94	91	91	86	74	73	66	75	85	86	88	77	85	78	68	83
	LNets+ANet [6]	**99**	91	98	95	**98**	95	96	93	79	79	68	78	90	91	92	81	89	82	71	87
	MT-RBM (PCA) [11]	97	90	98	96	96	**97**	96	94	77	81	69	81	88	95	96	86	92	81	87	87
	MCFA	**99**	**94**	**99**	**97**	**98**	**97**	**98**	**97**	**83**	**85**	**72**	**84**	**92**	**96**	**96**	**87**	**94**	**90**	**88**	**91**
LFWA	FaceTracer [20]	75	70	77	69	84	83	71	71	67	65	68	73	67	67	70	73	63	88	81	74
	PANDA-w [5]	78	64	82	65	86	77	68	70	63	63	64	71	63	65	64	68	61	85	79	71
	PANDA-l [5]	82	84	84	75	92	87	76	79	79	80	73	79	69	75	73	84	92	86		81
	ANet [21]	82	78	86	68	91	79	72	72	66	72	70	73	69	70	74	70	87	81		76
	LNets+ANet(w/0) [6]	84	81	83	75	91	87	72	76	78	79	72	76	79	70	74	77	81	90	83	79
	LNets+ANet [6]	88	**84**	88	78	**94**	**92**	77	79	**82**	**83**	75	**81**	**82**	73	**78**	81	85	**94**	88	**84**
	MCFA	**91**	75	**91**	80	93	91	**78**	**82**	79	79	**75**	**81**	76	**74**	77	78	**85**	93	**89**	**84**

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