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Facial Beauty Prediction and Analysis Based on Deep Convolutional Neural Network: A Review

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Abstract: Facial attractiveness or facial beauty prediction (FBP) is a current study that has several potential usages. It is a key difficulty area in the computer vision domain because of the few public databases related to FBP and its experimental trials on the minor-scale database. Moreover, the evaluation of facial beauty is personalized in nature, with people having personalized favor of beauty. Deep learning techniques have displayed a significant ability in terms of analysis and feature representation. The previous studies focussed on scattered portions of facial beauty with fewer comparisons between diverse techniques. Thus, this article reviewed the recent research on computer prediction and analysis of face beauty based on deep convolution neural network DCNN. Furthermore, the provided possible lines of research and challenges in this article can help researchers in advancing the state – of- art in future work.

Keywords: Facial beauty prediction, deep learning, convolutional neural network, transfer learning, generative adversarial networks

1. Introduction

There is a growing interest in the automatic human-like Facial Attractiveness Prediction (FAP) or Face Beauty Prediction (FBP) amidst the domain of machine learning and computer vision. This is expected to have wider application cases, including make-up evaluation, facial image beautification, content-based face retrieval, and social network recommendation systems, cosmetic recommendation, aesthetic surgery planning, entertainment, photo retouching, and among others [1],[2],[3]. Psychology research displayed a consistent beauty perception amidst diverse people. Moreover, a study showed a uniform concept in facial beauty, which can be learned through machines [4],[5]. Nevertheless, achieving an automatic facial attractiveness prediction is unnecessary for a stable perception of humans [6]. The problem is in two ways: at first, the human perception complexity and enormous facial appearance variance propel difficulty in the construction of robust and effective beauty assessment models. Secondly, a lot of facial benchmark databases are mainly structured for problems associated with facial recognition and can be useful in predicting attractiveness [7],[8].

Hönn *et al.* [9] presented a review to investigate a question related to the way facial attraction factors are adjustable relative to measurement. The available tools to carry out this measurement were also considered. The facial image determination, artistic standards, anthropometry, and cephalometry are explained. Besides, facial attractiveness is influenced by averageness, symmetry, and distinguishing attributes, including gender-specific features or dental aesthetics. Despite the extensive studies and continuous interest in social, evolutionary, and cognitive sciences, analysis and modeling of aesthetic canons and human beauty remain open. Gunes *et al.* [10] put beauty traits under the

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spotlight through the investigation of different parts of computations and perceptions. They presented human attractiveness enhancement and prediction are within infancy. At first, all theories of attractiveness have not been investigated about computation, enhancement, and prediction of human beauty. Additionally, studies have not been carried out on the main reason(s) for the achieved observer ratings. A review article was previously published on the advances in computational methods to facial attractiveness in [11].

Laurentini *et al.* [12] carried out a research survey on computer analysis of human beauty. The results of medicine and human sciences presented enormously shared and data-driven perception of attractiveness that is important to computer beauty analysis. Research surveys were also carried out on facial attractiveness in terms of automatic analysis. This review considered the recent research on FBP, discusses open problems and possible lines of research. It will serve as a starting point for the upcoming investigators to begin to improve their study on the art.

The rest of the paper is arranged as follows: Section2 presents a general structure of BFP and the benchmark dataset of PFB. Section 3 illustrates various DCNN used for BFP. Some of the facial beauty analysis and prediction challenges, and performance evaluation are laid in section 4. Finally, section 5 provides a discussion and draws the conclusion of this review.

2. Facial Beauty Prediction General Structure

Facial beauty classifications and attractiveness computations were established to develop automatic techniques in quantifying facial beauty through the fascial features and images and revealing the quantitative association between facial attractiveness perception and characteristics [13]. This is a new area of study that requires artificial intelligence, image processing, and pattern recognition. There are six general steps shown in Fig. 1 that are included in facial beauty prediction; as follows [11],[14],[15],[16]:

- **Database acquisition:** It is a crucial stage as it works as a basis for the computational models. In attractiveness research, acquiring the face data is in three ways: from the public face databases; different Internet resources and photographs generated through some software or digital cameras and 3D scanners.
- **Pre-processing:** Face data are obtained from different sources. Therefore, to standardize the face data, it is necessary to pre-process them. A model pre-processing approach includes rectification, noise removal, landmark localization, face cropping, intensity and scale, normalization concerning size, etc. Pre-processing has already been done in most publicly available face databases.
- **Beauty score database construction:** In BFP, the scarcity of universally accepted true beauty scores is a challenge. Surveying various human ratters in an ideal way will help derive a proxy for the ground truth. Ordinarily, a huge group of ratters will be requested to give their attractiveness scores to all the faces. A rating distribution analyzer is needed to confirm the statistical outcomes if it is enough to show the “collective beauty ratings”. There is a ground truth treatment for the average score of individual face to develop attractiveness models.
- **Feature extraction and selection:** This step determines the attributes or features used in developing the prediction model. The features are different as they may either be at the local or holistic scale. There are geometric, texture, and appearance feature-based[17],[18]. Furthermore, the most important features are determined from a large number of features in the selection process to predict the model.
- **Development of the prediction model:** Several methods based on statistics, machine learning, and deep learning are utilized to depict the facial representative features in scoring the attractiveness. For this purpose, diverse techniques have been used. These include the k-nearest neighbor's (KNN) algorithm, support vector machine (SVM), and deep convolutional neural network (DCNN). Moreover, data augmentation and pertained network techniques are sometimes utilized to enhance the accuracy of prediction.
- **Model validation:** After building the FBP model, it is critical to compare the human rate scores with the models’ scores to validate the predicted ratings.

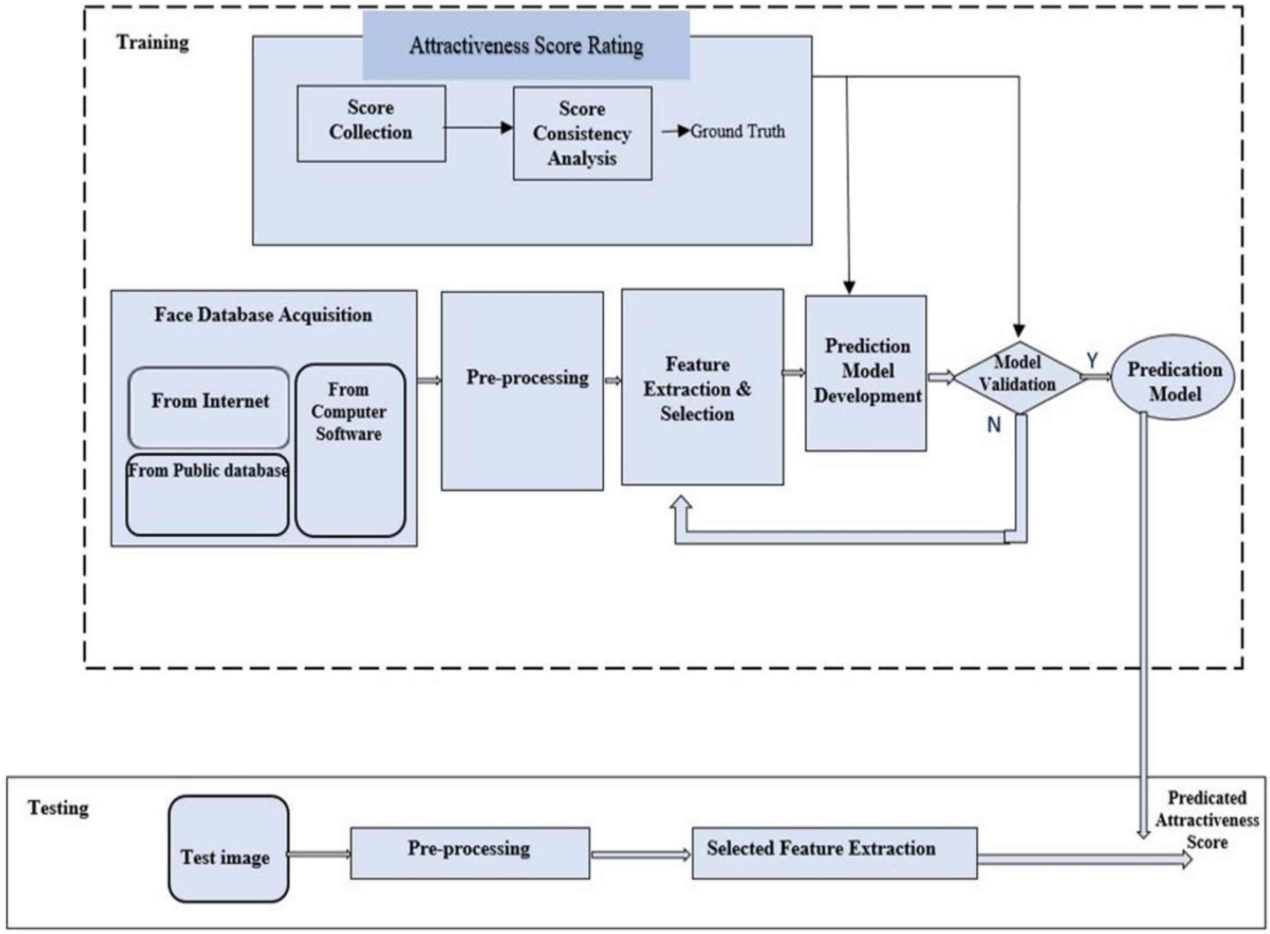

Fig. 1 - General structure of the prediction of facial attractiveness.

2.1 PFB Benchmark Dataset

Selecting an appropriate face database is essential in the generalizability and validation of the predicted model. Normally, the database should comprise different genders and faces of every level of attractiveness, age, and ethnicity [11]. Most of the recent FBP models are data-driven, making the benchmark dataset one of the essential elements for FBP [19]. Face image samples generated from diverse databases employed in the classification and prediction of face beauty are shown in Fig. 2.

- **Multi-Modality Beauty (M2B) dataset**: It comprises audio files, dressing images, and facial images of 1240 females. These images were ranked using different scores within an interval [1-10]. They were grouped into two ethnics: easterners and westerners (each group comprised 620 persons). The ratings were chosen among 40 participants [20],[21].
- **SCUT-FBP dataset**: It comprises about 500 Asian females of different origins and attractiveness rankings. These had been validated based on self-consistency, consistency, standard deviation, and rating distribution. The beauty scores (rankings) fell within an interval of [1-5], resulting from an average of diverse scores. The scores were generated from 75 persons through a web-based device, taking 70 raters per image as an average[19],[20],[22].
- **Large-Scale Asian Female Beauty Dataset (LSAFBD)**: It contains 20000 labeled images with 10000 unconstrained females and 10000 unconstrained male subjects, the beauty scores (rankings) fall with an interval of [1-5]. About 200 participants took part in the rating. Teachers and students between the ages of 20 and 35 were the most rating volunteers. All the images were validated using a well-designed rating with standard deviation and average scores [23].
- **Geometric Facial Beauty (GFB) dataset**: It contains 4905 males and 4510 females. The beauty scores (rankings) fall within an interval of [1-10]. It can be rated online using an SNS site [24].

- **SCUT-FBP5500 dataset**: It comprises 5500 frontals, neutral expression, and unclouded individuals' faces within 15 and 60 years of age. They were categorized into four subgroups with varied genders and traces. These include 2000 Asian males (AM), 2000 Asian females (AF), 750 Caucasian males (CM), and 750 Caucasian females (CF). Every image was labeled with beauty ratings within an interval of [1-5]. The ratings were collected among 60 participants [19],[20].
- **ECCV HotOrNot dataset**: It comprises 2056 faces obtained through the internet. This is a difficult benchmark dataset for predicting facial beauty. This is due to the cluttered background, variant postures, illumination, unaligned face problems, and low resolution that caused difficulty in predicting facial beauty. There were 2056 faces obtained from the internet in the dataset. An individual face was labeled using a rating; however, this dataset has been divided into test and training sets. The concluding result was determined using an average of 5-fold [16],[22],[25].

Fig. 2 - Samples of face images from the various databases used for prediction and classification of face attractiveness.

2.2 Performance Evaluation

As provided in Equations (1) and (2), the Pearson's correlation (PC) coefficient determines the linear correlation between the estimated labels and the ground truth to calculate the prediction performance [26].

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \qquad (1)$$

where n is the sample size, x_i and y_i are sample points, and

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i\ , \quad \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \qquad (2)$$

where r falls within −1 to 1 with the strongest positive linear correlation represented by 1, no correlation for 0, and −1 represents the strongest negative linear correlation.

Another measure is accuracy, as in Equation (3); it may be used to assess performance. True positives (TP) are positive cases that are correctly predicted, and false negatives (FN) are negative cases that are incorrectly predicted. True negatives (TN) are negative instances that are accurately predicted, and false positives (FP) are positive instances that are wrongly predicted [27],[28],[29].

$$\text{Accuracy}(\%) = \frac{\text{TP}+\text{TN}}{(\text{TP}+\text{TN}+\text{FP}+\text{FN})} \qquad (3)$$

3. FBP and Deep Learning Techniques

The conventional techniques are immensely handcrafted attribute-based [16],[30],[31],[32]; their attributes are structured based on limited evidenced and common cognition regulations associated with facial attractiveness based on both shape and texture [33],[34],[35]. Because the modeling of beauty is difficult using traditional techniques, this qualifies it as an adequate subject for data-driven techniques like deep learning [36]. Over time, different techniques and datasets of FBP had been proposed [37]. An amazing capacity had been obtained in deep learning techniques for feature analysis and representation [38].

3.1 FBP and Convolutional Neural Networks

CNNs' have displayed amazing facial comprehension results and recognition and had shown as efficient techniques for facial feature exploration [39],[40]. Facial beauty can be influenced by different qualities such as shape, color, geometric, and skin texture. The features are used to produce predictive model attractiveness, which is calculated from the facial images [11].

Zhang *et al.* [24] carried out a finding on the facial aesthetic perceptron to determine the importance of beauty using the geometric properties about collective attractiveness assessment technique. An example of geometric landmark representation is shown in Fig. 3. A geometric feature score function was quantitatively suggested for attractiveness assessment through the use of a model semi-supervised HSSL learning technique to produce a labeled unattractive and internet-labeled attractive faces. They created a beautiful facial dataset using annotated geometric landmark properties. Besides, this study used an existing M2B called multi-modal facial beauty dataset, and a semi-supervised scheme was favorable compared to many supervised schemes. This suggests that a semi-supervised scoring method opens doors to nearly every single technique to embrace continuous scoring instead of the usual discrete labels.

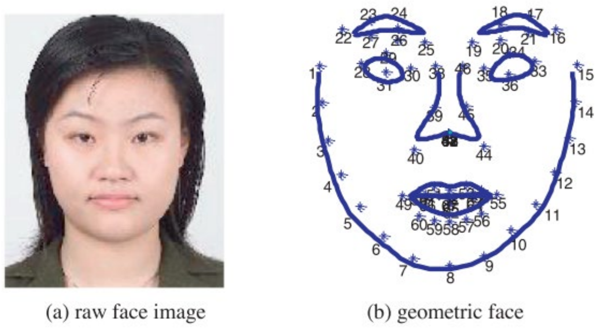

Fig. 3 - Geometric landmark representation example [24].

It has been established by Gao et al. [33] that deep multi-task learning techniques were used to solve automatic FAP problems. A study proposed a combined CNN model that takes geometric characteristics and appearance into consideration on a simultaneous benchmark SCUTFBP. Lin *et al.* [41] verified and established that it is significant to use the encoded ranking information in managing the study of the regression model of FBP. In the previous FBP model, the use of a design in ranking information when naively combined with the DNN structure of regression was ignored, and this may result in a wrong satisfactory outcome. Hence, it was suggested that R3CNN known as a general CNN architecture, can be used to enhance FBP performance by integrating the relative facial ranking in terms of aesthetics.

Currently, there are well-develop networks with high structures that can give better representation performances. The block's effectiveness depends on the design and not on the information transmission pathway's efficiency; this may result in a sub-optimal efficiency for future representation. Furthermore, Xu *et al.* [42] suggested that a PI-CNN was used to obtain an automatic facial beauty prediction. PI-CNN can be regarded as a hierarchical model that enables predictor training and facial beauty-representation learning. The current psychological findings showed important facial color and lighting characteristics to optimize the psychologically inspired convolutional neural network, facial beauty predictor, by utilizing a modern cascaded fine-tuning technique. However, the results illustrated that intensive learning possessed different types of applications in FBP. Contrary to face recognition, FBP still gives some difficulties, including lower accuracy, shallower depth CNN model, and smaller-scale database. A study carried out by Liang *et al.* [43] showed the facial recognition's invariant features resulted in a decrease in the variances produced by image translation and rotations, as shown in Fig.4.They introduced a new facial beauty prediction. A deep convolutional neural network is referred to as region-aware scattering convolution networks (RegionScatNet). The region-aware scattering convolution networks RegionScatNet are combined with the scattering transform and region-aware facial attributes decomposition. It obtains facial representation that is both invariant and discriminative for attractiveness examination, assessment, and variances due to rotation changes.

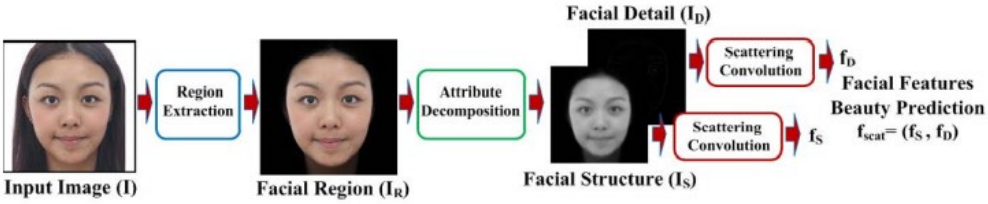

Fig. 4 - The architecture of Region ScatNet [43].

Gan *et al.* [44] proposed a solution to avert the problem by constructing a lighted DCNN for FBP with enhanced feature extraction, which utilizes GoogleNet's inception model as the first convolution layer to extract multi-scale face image features with enhanced feature extraction capability. Unlike the published CNN models such as VGG, GoogleNet, DeepID, and others, the LDCNN model can achieve more compact face image features and reduce the CNN model's parameters with the MFM, which is used by the competition mechanism to replace the ReLU activation layer.

Dornaika *et al.* [21] suggested that using semi-supervised learning schemes to solve facial beauty assessment is holistic when an image descriptor is a real number. They used graph-based semi-supervised learning to score facial attractiveness. This approach depended on the continuous use of full range and texture. Thereafter, kernelize, which was an existing linear Flexible Manifold Embedding scheme, was adapted to real score propagation. The obtained model can be employed for inductive and transductive settings.

Human beings are affected by the faces they had seen in the past, and this could influence their perception of facial beauty [16]. A study was proposed by Cao *et al*. [40] used a broad network design for FBP cases to achieve great performance. They introduced the use of an RIR (residual-in-residual) structure to the network when it passed through the gradient flow deeper to build a higher pathway where information can be transmitted. For a higher feature performance, the residual-in-residual structure for the deeper network should be created. Instead of using a residual-in-residual structure, they introduced an attention mechanism to obtain inner correlations among the properties. They also investigated a joint SCA block called spatial-wise and channel-wise attention, which helps distribute important information among features to obtain facial information for better representation. The results obtained showed that the suggested network predicted more facial beauty in humans than the state-of-the-art. In the case of BFP, they still face a lot of barriers due to the complexity of the deep structure network that requires high dimensions and a large number of parameters for easy time consumption.

Zhai *et al.* [45] provided a solution to the fast training FBP method's problems using BLS (broad learning system) and local feature fusion. They first introduced two 2DPCA called dimensional principal component analyses to decrease the local texture image's dimension, followed by reducing its redundancy. Moreover, the local feature fusion method was employed to achieve adequate advanced characteristics by keeping away the effects of various postures, individual differences, and unstable illumination. Lastly, the use of the extensional feature eigenvectors method was introduced to distribute the learning network for improved efficiency of the FBP model and effectively improve its preciseness and reduce operational time.

3.2 BFP and Transfer Learning

Transfer learning is an effective and simple method that improves a network from the target domain and transfer the parameters of a trained-related domain to the source domain. It is necessary to change the source domain's weight before it is discriminately utilized in the target domain. Transfer learning presents better performance than the scratch network because the pre-trained model had already possessed several basic information. Transfer learning helps in solving deficient specimen challenges of a small database and improves the model learning performance. Fig. 5 demonstrates the traditional machine learning versus transfer learning.

Xu *et al.* [22] suggested an approach that can move abundant deep features from a pre-trained model of the face assessment task and feed the features into a Bayesian ridge regression algorithm to forecast facial beauty. This method leverages the deep neural networks that can extract abstract features from the stacked layers. It achieves an effective and simple feature fusion technique through ECCV HotOrNot and SCUT-FBP datasets. Zhai *et al.* [46] showed promising results on fine-grained image classification using a multi-scale architecture to increase diversification among the deep features using BeautyNet to predict unconstrained facial beauty. A multi-scale network was used to enhance the discriminative features of the face. Also, it alleviates the computational burden of multi-scale architecture. Max-feature-map (MFM) was used as an activation function to increase the network convergence as well as improving its performance. Transfer learning technique was employed to reduce overfitting problems that occurred as a result of scarce labeled face beauty specimens and enhance the suggested BeautyNet's performance

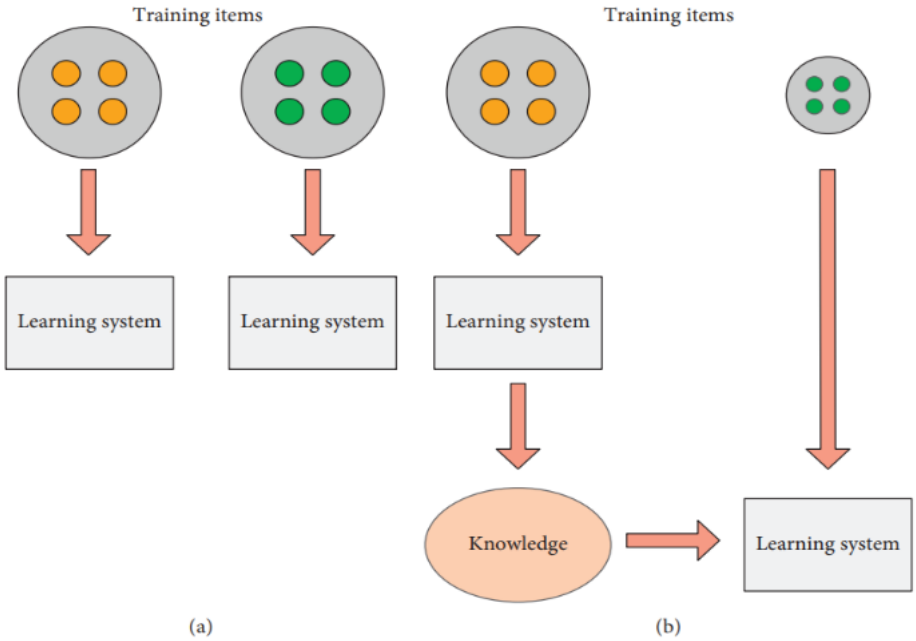

Fig. 5 - (a) Conventional ML; (b) Transfer learning [46].

Multi-task transfer learning uses auxiliary data of related tasks to solve the major task and effectively prevent overfitting. A multi-input multi-task beauty network can also be called 2M BeautyNet. It was used by Gan *et al.* [47] to predict face beauty using transfer learning. The gender recognition step was called the auxiliary, while beauty prediction was known to be the main task. Multi-task training assists in improving the performance of FBP using multi-task loss weights automatic learning methods. Then the Softmax classifier was replaced with a random forest.

Zhai *et al.* [48] proposed using a transfer learning-based CNN technique that allows various channel features to predict Asian female facial beauty. In the first instance, LSAFBD was created with a more reasonable distribution. Secondly, it was proposed that using a double activation layer and effective CNN called softmax-MSE loss function enhanced CNN's self-learning capacity in face beauty prediction. Furthermore, a transfer learning and data augmentation approach was employed to reduce the influence of inadequate information on the suggested CNN's performance. Multiple-channel feature fusion strategies were also employed to assist in optimizing the proposed CNN. The achieved results showed that the suggested technique is better than the traditional learning approach in overcoming the Asian female FBP task.

3.3 BFP and Generative Adversarial Networks (GANs)

Nowadays, generative adversarial networks are largely investigated; the results showed that GANs could create highly realistic images from scratch [49],[50]. One of the major difficulties in learning facial beauty is that it must be carried out in an unsupervised manner because there are no fewer or more pairs of attractive images of an equal individual that may require supervised learning [51]. Diamant *et al.* [37] created face images based on the condition of their beauty score. Their work trained a generative model to achieve facial image conditions on a demanded beauty score. Moreover, the trained generative model could be utilized in the beautification of input face images. Unsupervised beautification model does not depend on the truth target facial images that have been established. A novel study was proposed by Liu *et al.* [52] using a mining beauty semantics of facial features. they relied on big data to construct descriptions of beautiful faces in quantitative and objective manners. They utilized a deep CNN to achieve facial features and to detect the correlations between attractiveness and attributes on two large-scale datasets labeled with beauty scores. The secret of beauty was discovered and verified using statistical significance tests, which also perfectly aligned with observing psychological studies such as femininity, high cheekbone, and small nose contribute to attractiveness. GAN method was utilized to leverage these high-level representations to the original facial images. After synthesizing beauty enhancements, they are statistically convincing and compelling, which are verified using a user survey of about 10,000 data points. Fig. 6 shows some samples of modified facial attributes, while Table 1 summarizes the recent models of BFP based on a variety of DCNN.

Table 1 - A summary of the recent models of BFP based on DCNN.

Ref.	Dataset	Beauty Score	Raters No.	Gender	Metrics		Limitation(s)
[24]	GFB M2B	1-10	SNS site	Both	The subjective evaluation experiments are not conducted in this article.		-It doesn't consider the variation of facial expression.
[42]	SCUT-FBP	1-5	75	Female	PC	0.87	-A large-scale benchmark database for BFP is needed to tackle the benchmark evaluation problem. -Gender-specific model using female images only.
[43]	SCUT-FBP	1-5	75	Female	PC	0.83	- In certain cases, it is difficult to interpret the discriminatory features of a CNN-based function. - Constrains the predictor to Asian female faces.
[33]	SCUT-FBP	1-5	75	Female	PC	0.92	- Instead of a label-distribution learning (LDL) method, a regression was performed. This shows significantly better results than [53, 54]. - Gender-specific model that only uses female images.
[41]	SCUT-BP5500 SCUT-FBP	1-5	60 75	Both	PC	0.9052	-label distribution learning (LDL) [54] is slightly better than this method in terms of MAE and RMSE.
[44]	LSAFBD	1-5	30	Female	Accuracy	63.5%	- As the average of rated values of 30 raters has been rounded to an integer, prediction values fluctuate up and down at rated values so that there is a certain distortion in the rated values. -Gender-specific
[45]	LSAFBD	1-5	30	Both	Accuracy	58.97%	-Cost-sensitive problem of facial beauty needs to be solved.
[21]	SCUT-FBP, M2B, SCUT-BP5500.	1-5 1-10 1-5	75 40 60	Both	PC	86.60	-The prediction accuracy is affected by the graph quality.
[40]	SCUT-FBP5500	1-5	20	Both	PC	0.9003	- Training labels are assessed by some students in a particular culture, which does not have a common opinion. -The trained images are chosen from Asian and Caucasian individuals, which may contribute to bias on diversity.
[45]	LSAFBD	1-5	A/N	Both	Accuracy	58.97%	- The cost-sensitive facial beauty dilemma needs to be solved in the future.
[22]	SCUT-FBP ECCVHotOr Not	1-5	10	Female	PC PC	0.8570 0.468	-Face alignment is not considered. -Gender-specific female only.

[46]	LSFBD CASIA	1-5	A/N	Female	Accuracy	67.48%	-Further exploration is required for the unconstrained facial beauty prediction task. -Gender-specific, female only.
[47]	LSFBD SCUT-FBP5500	0-4	60	Both	Accuracy	68.23%	- It needs a more robust and powerful multi-input multi-task network.
[48]	LSAFBD CASIA-WebFace	1-5	200	Female	PC	0.8829	-Suitable for western faces may not apply to the east.
[37]	SCUT-FBP5500	1-5	A/N	Both	PC	0.79	-With improving the beauty level, it seems that personal identity is not preserved.
[52]	Beauty 799 The 10k US	1-3 1-5	25 12	Both	Accuracy	96.5%	-Semantics are not exactly the same between these two databases.

Fig. 6 - In the individual group, the left relates to the original image, and the right indicates the synthesized one. The sample modified facial features from left to right are male to female, small to the big nose, young to aged, and no-makeup to make-up.

4. Some Challenges in Facial Beauty Analysis and Prediction

Beauty is an abstract concept that humans can easily recognize but hard to be learned by the machine. The area of facial attractiveness has been focused upon by philosophers, artists, and scientists for years. The physical attractiveness rules have been widely studied, and recent studies have shown some common features involved in achieving facial attractiveness [55]. Moreover, the prediction of facial attractiveness has received enormous interest from the image processing community. Despite the substantial results from the previous studies, several problems are still being faced. Based on the current research background, FBP has some issues and limitations as follows:

- **Accurate Representation for Facial Composition:** The inadequate representation of facial composition is essential for determining attractiveness [56]. A large number of recent methods were done using the 2D frontal view of faces. However, human faces are 3D in the structure; human visual compartments are stereoscopic and can adequately capture 3D structures. In general, substantial information on facial attractiveness and faces are not considered in some recent studies [10],[11].
- **Databases Size and Diversity:** A dataset for the study of facial beauty needs to have substantial variations based on attractiveness. No previous open-face databases have been carried out by taking into account this requirement. A small portion of beautiful faces exists in databases, with most of the faces generated from confined ethnic groups. Previous findings have shown that deeper representation has higher efficient performance than inadequate ones [46, 57]. The solution to this inadequacy is to employ state-of-the-art techniques such as data augmentation or transfer learning so as to improve the most and least attractive faces [21],[22],[47].
- **The Number of Human Raters:** A small number of raters may not show an accurate estimate of attractiveness because the rankings differ mainly on several parameters such as genders and ethnicity for both face samples and raters. Thus, an average ranking from a small set of raters may not be an adequate representation of general preference for attractiveness [2], [24],[57].

- **Face gender impact:** Several studies employ either images from both gender or only female images; however, a few studies still use male data. This concludes the hypothesis that female beauty might be easier to analyze and compute compared to male [58].
- **Face poses and expressions:** The majority of the previous studies were carried out on faces with near frontal or frontal views and faces with neutral or little expression [59].

5. Conclusion and Discussion

Philosophers and psychologists have previously discussed the concept of beauty; however, most explanations are metaphysical and subjective and lack scalability, generality, and accuracy. The theoretical outcomes from FBP studies have been mostly employed in areas like beauty product shopping guides, cosmetic surgery, and social applications. Nevertheless, FBP lacks issues such as inadequate high-performance equipment, the long training time of deep networks, and unclear evaluation indicators. To tackle inadequate labeled data and train their systems, semi-supervised learning and/or data augmentation either by flipping, rotation, etc., or GAN could be used. In addition, building an outstanding dataset for the FBP problem with a variety of genders, ages, cultures, ethnicities, different expressions, poses, traditions, and economic status is essential. Furthermore, studies should concentrate more on 3D frontal and profile view of faces for more representation and use of varied rating methods such as social networking service. Moreover, the diversity of raters' age, gender, race, and ethnicity should be taken into consideration. This paper has reviewed the state-of-the-art in the area of beauty face prediction and provided a distinct outlook for future studies.

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References

[1] Deias, A.E., Face beauty analysis via manifold based semi-supervised learning. 2017
[2] Eisenthal, Y., G. Dror, and E. Ruppin, Facial attractiveness: Beauty and the machine. Neural Computation, 2006. 18(1): p. 119-142
[3] Hong, Y.-J., et al., A Novel Framework for Assessing Facial Attractiveness Based on Facial Proportions. Symmetry, 2017. 9(12): p. 294
[4] Bottino, A. and A. Laurentini. The analysis of facial beauty: an emerging area of research in pattern analysis. in International Conference Image Analysis and Recognition. 2010. Springer
[5] Gan, J., L. Zhou, and Y. Zhai. A study for facial beauty prediction model in 2015 International Conference on Wavelet Analysis and Pattern Recognition (ICWAPR). 2015. IEEE
[6] Xu, M., et al., Bio-inspired deep attribute learning towards facial aesthetic prediction. IEEE Transactions on Affective Computing, 2018
[7] Knight, H. and O. Keith, Ranking facial attractiveness. The European Journal of Orthodontics, 2005. 27(4): p. 340-348
[8] Young, P.A., Concepts of Facial Beauty, in Rhinology and Facial Plastic Surgery. 2009, Springer. p. 819-830
[9] Hönn, M. and G. Göz, The ideal of facial beauty: a review. Journal of Orofacial Orthopedics/Fortschritte der Kieferorthopädie, 2007. 68(1): p. 6-16
[10] Gunes, H. A survey of perception and computation of human beauty in Proceedings of the 2011 joint ACM workshop on Human gesture and behavior understanding. 2011
[11] Liu, S., et al., Advances in computational facial attractiveness methods. Multimedia Tools and Applications, 2016. 75(23): p. 16633-16663
[12] Laurentini, A. and A. Bottino, Computer analysis of face beauty: A survey. Computer Vision and Image Understanding, 2014. 125: p. 184-199
[13] Rhazi, M.E., et al., Facial beauty analysis by age and gender. International Journal of Intelligent Systems Technologies and Applications, 2019. 18(1-2): p. 179-203
[14] Kagian, A., et al. A human-like predictor of facial attractiveness in Advances in Neural Information Processing Systems. 2007
[15] Hou, J., S. Yang, and W. Lin. Object-level Attention for Aesthetic Rating Distribution Prediction in Proceedings of the 28th ACM International Conference on Multimedia. 2020
[16] Gray, D., et al. Predicting facial beauty without landmarks in European Conference on Computer Vision. 2010. Springer
[17] Mahmood, M.R. and A.M. Abdulazeez. Different Model for Hand Gesture Recognition with a Novel Line Feature Extraction in 2019 International Conference on Advanced Science and Engineering (ICOASE). 2019. IEEE

[18] Mahmood, M.R. and A.M. Abdulazeez. A Comparative study of a new hand recognition model based on line of features and other techniques in international Conference of reliable information and communication technology. 2017. Springer
[19] Liang, L., et al. SCUT-FBP5500: a diverse benchmark dataset for multi-paradigm facial beauty prediction in 2018 24th International Conference on Pattern Recognition (ICPR). 2018. IEEE
[20] Dornaika, F., et al., Efficient deep discriminant embedding: Application to face beauty prediction and classification. Engineering Applications of Artificial Intelligence, 2020. 95: p. 103831
[21] Dornaika, F., et al., Toward graph-based semi-supervised face beauty prediction. Expert Systems with Applications, 2020. 142: p. 112990
[22] Xu, L., J. Xiang, and X. Yuan, Transferring rich deep features for facial beauty prediction. arXiv preprint arXiv:1803.07253, 2018
[23] Zhai, Y., et al. Benchmark of a large scale database for facial beauty prediction in Proceedings of the 2016 International Conference on Intelligent Information Processing. 2016
[24] Zhang, L., et al., Facial beauty analysis based on geometric feature: Toward attractiveness assessment application. Expert Systems with Applications, 2017. 82: p. 252-265
[25] Xu, L., J. Xiang, and X. Yuan. Crnet: Classification and regression neural network for facial beauty prediction in Pacific Rim Conference on Multimedia. 2018. Springer
[26] Tutorials, S., Pearson correlation. Retrieved on February, 2014. 4
[27] Abdulrazzaq, M.B. and J.N. Saeed. A Comparison of Three Classification Algorithms for Handwritten Digit Recognition in 2019 International Conference on Advanced Science and Engineering (ICOASE). 2019. IEEE
[28] Zeebaree, D.Q., et al. Trainable Model Based on New Uniform LBP Feature to Identify the Risk of the Breast Cancer in 2019 International Conference on Advanced Science and Engineering (ICOASE). 2019. IEEE
[29] Saeed, J.N., A Survey of Ultrasonography Breast Cancer Image Segmentation Techniques. 2020: Infinite Study
[30] Yan, M., et al. Facial beauty assessment under unconstrained conditions in 2016 8th international conference on electronics, computers and artificial intelligence (ECAI). 2016. IEEE
[31] Chen, F., et al. Comparison and fusion of multiple types of features for image-based facial beauty prediction in Chinese Conference on Biometric Recognition. 2017. Springer
[32] Zebari, R., et al., A Comprehensive Review of Dimensionality Reduction Techniques for Feature Selection and Feature Extraction. Journal of Applied Science and Technology Trends, 2020. 1(2): p. 56-70
[33] Gao, L., et al. Automatic facial attractiveness prediction by deep multi-task learning in 2018 24th International Conference on Pattern Recognition (ICPR). 2018. IEEE
[34] Abdulqader, D.M., A.M. Abdulazeez, and D.Q. Zeebaree, Machine Learning Supervised Algorithms of Gene Selection: A Review. Machine Learning, 2020. 62(03)
[35] Zeebaree, D.Q., et al. Machine learning and Region Growing for Breast Cancer Segmentation in 2019 International Conference on Advanced Science and Engineering (ICOASE). 2019. IEEE
[36] Zeebaree, D.Q., H. Haron, and A.M. Abdulazeez. Gene selection and classification of microarray data using convolutional neural network in 2018 International Conference on Advanced Science and Engineering (ICOASE). 2018. IEEE
[37] Diamant, N., et al. Beholder-GAN: Generation and beautification of facial images with conditioning on their beauty level in 2019 IEEE International Conference on Image Processing (ICIP). 2019. IEEE
[38] Ahmed, O. and A. Brifcani. Gene Expression Classification Based on Deep Learning in 2019 4th Scientific International Conference Najaf (SICN). 2019. IEEE
[39] Zhang, Y., W. Ding, and C. Liu. Summary of Convolutional Neural Network Compression Technology in 2019 IEEE International Conference on Unmanned Systems (ICUS). 2019. IEEE
[40] Cao, K., et al., Deep Learning for Facial Beauty Prediction. Information, 2020. 11(8): p. 391
[41] Lin, L., L. Liang, and L. Jin, Regression guided by relative ranking using convolutional neural network (R3CNN) for facial beauty prediction. IEEE Transactions on Affective Computing, 2019
[42] Xu, J., et al. Facial attractiveness prediction using psychologically inspired convolutional neural network (PI-CNN) in 2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). 2017. IEEE
[43] Liang, L., et al. Region-aware scattering convolution networks for facial beauty prediction in 2017 IEEE International Conference on Image Processing (ICIP). 2017. IEEE
[44] Gan, J., et al., Facial Beauty Prediction Based on Lighted Deep Convolution Neural Network with Feature Extraction Strengthened. Chinese Journal of Electronics, 2020. 29(2): p. 312-321
[45] Zhai, Y., et al., Facial Beauty Prediction via Local Feature Fusion and Broad Learning System. IEEE Access, 2020
[46] Zhai, Y., et al., BeautyNet: Joint multi-scale CNN and transfer learning method for unconstrained facial beauty prediction. Computational intelligence and neuroscience, 2019. 2019
[47] Gan, J., et al., 2M BeautyNet: Facial Beauty Prediction Based on Multi-Task Transfer Learning. IEEE Access, 2020. 8: p. 20245-20256

[48] Zhai, Y., et al., Asian Female Facial Beauty Prediction Using Deep Neural Networks via Transfer Learning and Multi-Channel Feature Fusion. IEEE Access, 2020. 8: p. 56892-56907
[49] Sattigeri, P., et al., Fairness GAN: Generating datasets with fairness properties using a generative adversarial network. IBM Journal of Research and Development, 2019. 63(4/5): p. 3: 1-3: 9
[50] Radford, A., L. Metz, and S. Chintala, Unsupervised representation learning with deep convolutional generative adversarial networks. arXiv preprint arXiv:1511.06434, 2015
[51] Sulaiman, D.M., et al. Unsupervised Learning Approach-Based New Optimization K-Means Clustering for Finger Vein Image Localization in 2019 International Conference on Advanced Science and Engineering (ICOASE). 2019. IEEE
[52] Liu, X., et al. Understanding beauty via deep facial features in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops. 2019
[53] Liu, S., et al. Facial attractiveness computation by label distribution learning with deep CNN and geometric features. in 2017 IEEE International Conference on Multimedia and Expo (ICME). 2017. IEEE
[54] Fan, Y.-Y., et al., Label distribution-based facial attractiveness computation by deep residual learning. IEEE Transactions on Multimedia, 2017. 20(8): p. 2196-2208
[55] Rizvi, Q.M., A. Karawia, and S. Kumar. Female facial beauty analysis for assesment of facial attractivness in 2013 2nd International Conference on Information Management in the Knowledge Economy. 2013. IEEE
[56] Shi, S., et al. Improving facial attractiveness prediction via co-attention learning in ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). 2019. IEEE
[57] Zhang, D., F. Chen, and Y. Xu, Computer models for facial beauty analysis. 2016: Springer
[58] Fellous, J.-M., Gender discrimination and prediction on the basis of facial metric information. Vision research, 1997. 37(14): p. 1961-1973
[59] Whitehill, J. and J.R. Movellan. Personalized facial attractiveness prediction in 2008 8th IEEE International Conference on Automatic Face & Gesture Recognition. 2008. IEEE