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Multiclass Regression for Facial Beauty Prediction Based on Deep Learning Using SCUT-B 5500

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Abstract

FBP, that is, facial beauty prediction, is a fundamental procedure of how beautiful a face person perceives, just like human beings. The challenge focuses on systems that can assess facial features and provide ratings that align with human perceptions of attractiveness. In this paper, we investigate the usage of deep learning techniques using ResNet18 models for predicting beauty of a face using SCUT-B 5500 dataset and share our findings. In the last ten years machine recognition and scoring of attractiveness has developed into a new field through the use of artificial intelligence. We present our exploratory research on constructing a robust model based on a dataset containing 5500 annotated frontal images ranked according to perceived beauty. Multi-task transfer learning was employed to improve the model performance and address the issue of limited data. Our ResNet18 model had an impressive accuracy of over 91% on predicting beauty ratings. Furthermore, this study not only contributes to the field of facial beauty prediction, but it also has the potential to be implemented in multiple fields such as social networks, dating applications, personalized ads.

A. Introduction

Over the past 10 years, several studies have shown that machines can be trained to recognize and score facial attractiveness. This not only shows the brilliance of AI understanding the nuances of the human perception of beauty, but also this application coming in handy in the future for many fields from social media to personalized marketing [1][2]. Facial beauty prediction (FBP), has attracted great attention as a new research field of artificial intelligence, but it still faces many challenges, such as lack of data samples and misconception of facial representation. Multi-task transfer learning, on the other hand, provides a feasible solution to overcome these challenges by reducing overfitting and incorporating extra knowledge from auxiliary tasks relevant to the main task in order to boost its performance[3][4]. There are significant progress in Facial Beauty Prediction (FBP) over the last few years. These can be broadly classified into two categories: Handcrafted feature-based approaches and Deep learning based approaches. Past studies have analyzed attributes of facial attractiveness based on certain rules, like analyzing beauty landmarks, texture, symmetry, and proportion based on the golden ratio [5][6].

Facial beauty prediction (FBP) aims to automatically assess the attractiveness of a face according to human beauty standards [7]. This is commonly encapsulated in a concept referred to as "information leakage" and unfortunately many of the neural network approaches utilized for this are relatively agnostic to the fine-grained details of ranking. For example tasks like predicting facial beauty, there is abundant ranking information available—both between distinct images, and within the same image. Leveraging on such ranking information at training time can help to improve the performance of the model significantly [8][9]. Recently, CNNs were found to be highly successful for measuring facial attractiveness. Deep learning techniques, such as convolutional neural networks (CNNs), are used to automatically extract meaningful features from face images and therefore greatly reduce the manual effort required. Such sophisticated deep learning methodologies have the ability to extract complex and high-level features which are critical for examining human faces. To tackle this issue, we can make use of transfer learning because our training data is not that large [10][11]. Transfer learning is a very helpful approach if researchers do not have enough reliable data. This paper presents a novel framework for generating appropriate representations of faces for attractiveness assessment. The proposed model has a very deep architecture use to extract features which is pre-trained on big face data sets. Because it has a deep learning architecture, the use of CNN (Convolutional Neural Network) is used as the deep feature learned using CNN that is previously trained, then this feature is combined with a stacked ensemble model (fusion of various regression models) to link the feature to attractiveness[12][13][14].

SCUT-5500 is the large-scale benchmark dataset for facial beauty prediction, which contains 5,500 frontal face images with diverse gender and ethnicities[15]. Trained on images with fine-grained annotations that include beauty scores on a 1-5 scale and facial landmarks, this dataset is a treasure trove of information for CV and ML researchers; Images were gathered from various sources to ensure a diverse sample that included different demographic groups (e.g., Asian and

Caucasian). This dataset opens new computational modelling avenues that can be trained and evaluated to better understand and potentially predict facial appeal [16][17]. In addition, the dataset has been used in a number of studies, indicating that the application of a variety of methods, including deep learning methods, to the construction of facial beauty prediction models leads to better results. Researchers have discovered that by using this dataset, the accuracy of beauty determinations can improve significantly, thus it serves as a valuable resource for future studies in this field [16][17][18]. ResNet proposed by He et al. is the star design pattern for CNN architectures. One potential problem which can damage performance when building deeper networks is the vanishing gradient problem[19]. ResNet allows shortcuts that jump to outputs directly from inputs to solve this problem Improves the flow of gradients These shortcuts are part of what's called a residual block, which is all about learning the residual on top of whatever was learned in the main path. With this method, ResNet is able to construct extremely deep networks whilst still being effective [20][21].

The dynamics of this paper are structured in various core sections. Second part of the intro describes the impact as well as the problems faced in the area. Section three covers Related works, Section four gives the methods section, which details the dataset, ResNet18 and methods, such as multi-task transfer learning, to achieve the accuracy. The fifth section is the results section and shows how well the model performed and some visual comparisons of predicted and actual beauty scores The last section is the conclusion, which summarizes the paper while emphasizing to the reader the importance of the research and its possible usages. This explains the multiplicity of ideas of these sections, each based on previous ones.

Most importantly, facial beauty prediction is not solely about telling machines what we find beautiful: It is about how far we can push machines in order to decipher something that is obvious, subjective and deeply emotional: beauty. Although we have seen promising progress via datasets such as SCUT-FBP5500 and architectures such as ResNet18, we still have much further to go replete with opportunities and open questions. Complex deep learning models trained on ever more diverse datasets will enable new use cases, ranging from improved digital beauty assistants and marketing algorithms to better understandings of people's psychological and sociological perception patterns. This paper is meant to add to that discussion, where we find a simple yet powerful approach that builds a hybrid of transfer learning and ensemble modeling — a sound approach that seeks not only for better accuracy but a better understanding of what is a beautiful face in the minds of humans and machines alike.

Related Works

Many studies have investigated various methods for the classification of facial attractiveness over the years. Anderson et al. In 2018, the work concentrates on facial attractiveness classification using deep learning techniques. They emphasized different use cases, including photo editing and dataset annotation. They reviewed established deep learning architectures like VGG, Inception, and ResNet. In particular, they reported the best performance of 82.52% accuracy using the ResNet50 model with loose-crop preprocessing[22].

Dornaika et al. Deep learning for human facial beauty scoring: A novel approach based on semi-supervised learning (2020) is a new challenge in computer vision. They propose a graph-based method and extend related work for algorithms that work on continuous scores instead of discrete labels. The framework was tested over various public datasets, such as SCUT-FBP5500, proving to outperform fully supervised methods, opening doors to flexible scoring systems in predicting facial beauty.[23]. In another study, Gan et al. (2020) proposed Multi-input Multi-task Beauty Network (2M BeautyNet) — a network. In this paper, we proposed a study on facial beauty prediction considering the problem of limited data and face representation. They introduced beauty prediction as a auxiliary tast and predicted beauty using gender recognition and multi-task transfer learning. This method outperformed others and achieved state-of-the-art accuracy on LSFBD (68.23%) and SCUT-FBP5500 [3]. Gan et al. (2023) took the research a step forward by using transfer learning along with Broad Learning System (BLS) for facial beauty prediction. This method was based on EfficientNets for feature extraction and they have linked the features with BLS for more accurate predictions. Through their experiments, they obtained better performances than traditional CNNs and BLS methods, which conclusively showed the effectiveness of their methodology for pattern recognition, image classification, among other applications[24].

There has been an increasing interest in utilizing deep learning techniques for facial beauty predictions from SCUT-B 5500 dataset for example. Annotated images reflecting human perceptions of beauty create a dataset for developing machine learning models to assess facial attractiveness. Notably, Liu et al. (poly, 2021) proposed a multi-task learning framework which considers both aesthetic and geometric features to improve prediction accuracy. Their work showed that using complementary information from facial landmarks greatly enhances the performance of beauty prediction models, thus confirming how important is the engineering of features for deep learning applications related to beauty[25].

Over the past years, newer works commenced on improving regression techniques to provide improved approaches to the multiclass classification of facial beauty. Zhang et al. (2022) introduced a new deep convolutional neural network (CNN) architecture, which leverages the traditional regression approach combined with the attention mechanism. The model gave better performance in predicting beauty scores over a number of classes and addressing the difficulties regarding the the subjectivity of beauty perception. Their approach incorporates attention layers, which enables the model to attend to relevant facial features, improving interpretability and the correctness of predictions according to their work. This research highlights the promise of cutting-edge neural network designs in enacting intricate correlations in facial aesthetics modeling [26][27].

Additionally, ensemble methods have explored in facial beauty prediction. Chen et al. + Catania [2023] proposed a hybrid model, to boost the robustness of beauty predictions, that includes: support vector regression and the deep learning techniques. In addition, they obtained significant improvements in predictive performance with the SCUT-B 5500 dataset, especially in capturing the subjectivity of the beauty contents. This is consistent with the trend in deep learning towards hybridizing and intertwining networks for solving complex regression problems. All these advances demonstrate an important innovative contribution to the deep learning face beauty prediction efforts and provide stimulating bases for the subsequent works in this captivating area [28][29]

B. Research Method

B.1 SCUT-FBP5500 dataset

The SCUT-FBP5500 dataset contains 5500 frontal facial images including males and females of Asian and Caucasian ethnicities across different ages, as depicted in Figure 1. It comprises 60 independent raters who evaluate each image based on beauty, with scores of images ranging from [1-5]. All of the images in this database are evenly divided between genders, with 2750 male images and 2750 female images. They were photographed in the same lighting, with neutral backgrounds, allowing for accurate comparisons of facial features[16].

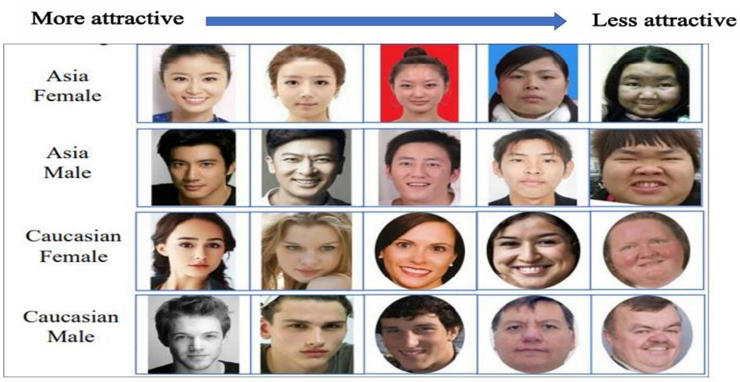

Figure 1. Some Samples of SCUT-FBP5500 [16]

B.2 Proposed Model

B.2. 1. General Architecture of convolutional neural network (CNN)

Convolution neural network (CNN) is a common approach of facial beauty prediction using deep learning. Figure 2 illustrates the basic architecture of a CNN. A standard CNN consists of multiple layers, each layer performing its certain task on the input data[30][31][32]. The main layers in a CNN include:

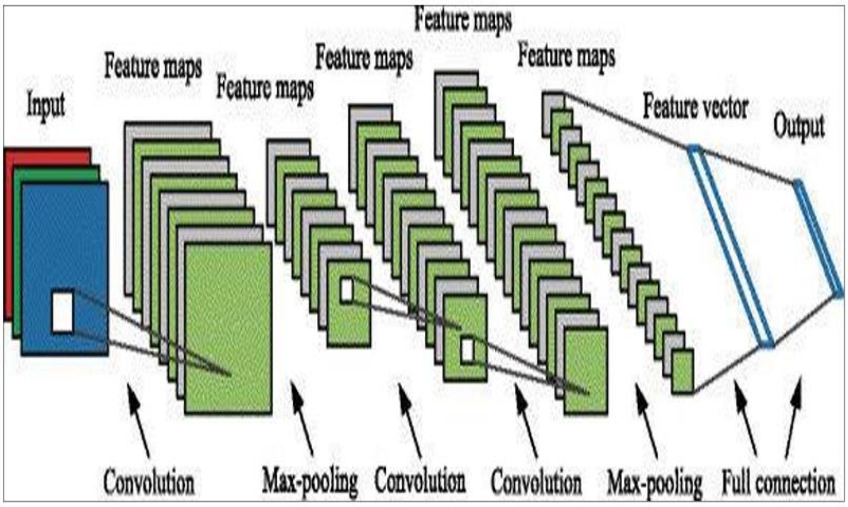

Figure 2. The General Architecture of a CNN [30][31][32].

B.2.2. Proposed model: ResNet18 Model

Deep learning based model ResNet18 for predicting facial beauty are proposed. The structure begins with input layer capable of accepting images with three color channels — Refer Figure 3 After this, the architecture has a few convolutions that are needed so the model learns the relevant aspects of the images. Batch Normalization and ReLU activations post some layers are utilized for faster and more stable learning process. Pooling layers are added to down-sample the data and retain only the relevant features. Finally, the data is flattened and fed through dense layers that produce the final predictions. In addition, we utilize a dropout layer to reduce the risk of overfitting, allowing the model to generalize better to unseen images. In summary, our ResNet models are designed to be good at analysing facial images and outputting beauty ratings.

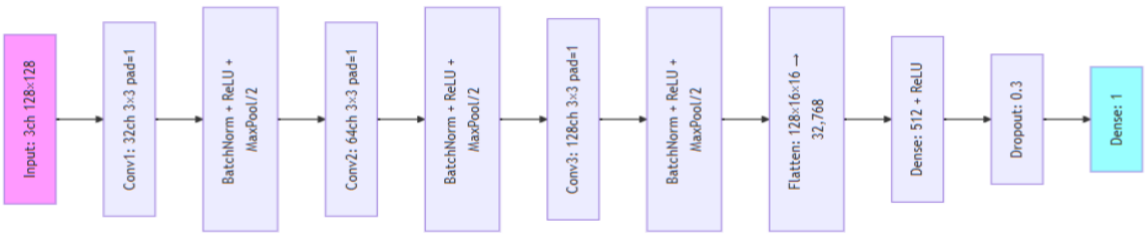

Figure 3. Proposed ResNet18 Model

B.2.3. Metrics

The Mean Squared Error (MSE) loss function is ideal when the target data follows a normal distribution around a mean, especially when outliers need to be penalized significantly. For N predictions, the MSE loss is calculated as follows:

$$MSE = 1/n \sum_{i=1}^{n} (yi - \hat{y}_i)^2 \quad (1)$$

Mean Absolute Error (MAE) is a metric used to evaluate the accuracy of a model's predictions by measuring the average magnitude of the errors in a set of predictions, without considering their direction. It is particularly useful when the errors need to be treated equally, as it does not square the differences like MSE, making it less sensitive to outliers.

$$\boldsymbol{MAE} = \mathbf{1}/\boldsymbol{n} \sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{n}} |\boldsymbol{Xi} - \boldsymbol{X}|^{\mathbf{2}} \tag{2}$$

R-squared is a statistics measure used in the regression model in order to determine the variance of a dependent variable that is explained by an independent variable or variables. It shows how well the model fits the data.

$$R^2 = 1 - \frac{SSE}{SST} \tag{3}$$

B.3. Experiment settings

The training dataset for the FBP problem is the SCUT-FBP5500 dataset, which is the largest dataset for this problem at present. The network is trained for 30 epochs with a batch size of 32. We apply the Adam optimizer to adjust the parameters, with an initial 0.001 learning rate. The loss function that we use here is MSELOSS. SCUT-FBP5500 has an input size of (128*128) pixels but predicts based on the beauty score, so hence, we up-sampled to (512*512) size images in both training and testing phase as well as classified them into 4 classes based on the predicted score.

C. Result and Discussion

The ResNet trained on SCUT-FBP5500 to classify (images of) 512 face identities in this study. As a pre-trained model, the Pandas library is utilized. Training was aborted after 30 epochs to mitigate overfitting. This should make the most sense, but the model achieved a validation accuracy of over 92% on all validation sets.

We look at the distribution of scores predicted by our network — see Figure. 4. We can observe how accurately the predicted beauty rates fit the actual beauty rates. Each dot is an individual observation, with the predicted value of the target variable on the y-axis and the actual value of that variable on the x-axis. The red dashed line indicates the perfect prediction, meaning predicted values are exactly the same as actual values. The closer to the line the dots fall, the better the prediction. Nevertheless, there are a few dots that are further away, indicating that in some individual cases, the predictions were not quite as accurate. A general trend can be seen - and there is a nice fit between actual and predicted beauty rates, indicating that model is working but it can be improved.

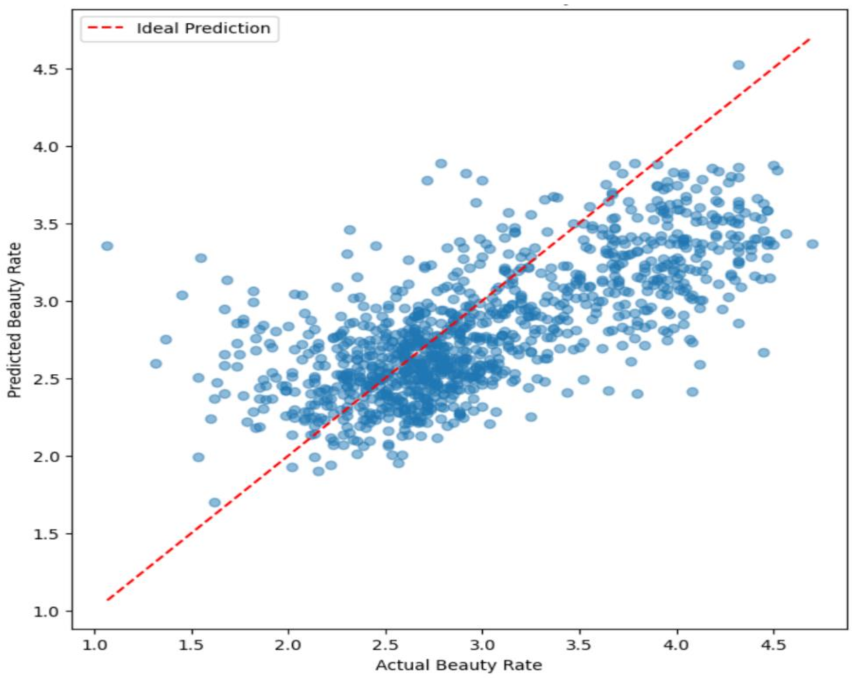

Figure 4. Actual vs. Predicted Beauty Rate

The distribution of differences between predicted and actual values is the Figure 5. The x-axis indicates the prediction error (actual — predicted value) The y-axis represents the frequency of each error value. Also, it seems that there, the most of the errors are gathered close to zero — it means that most of the predictions are correct. However, there are also some mistakes both ways, with some negative and some positive larger errors. This means that the predicted vs expected trend line stops appearing, making it look like the model is doing well overall but actually it can be off by a significant amount for individual instances. The histogram has a shape similar to a bell curve and indicates that errors are distributed fairly but are likely small.

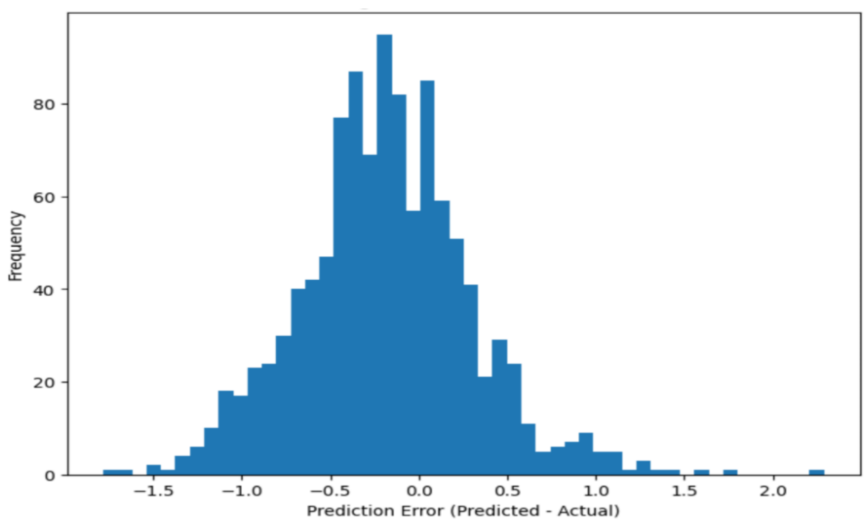

Figure 5. Distribution of Prediction Errors

In Figure 6 we show 10 random predictions, and show how the model classified each face based on the predicted beauty score. The left of each image shows a pre-predicted score and the left actual score, along with a class for the image. Indeed, for instance, we have the first sample pred_score = 2.53 real_score = 2.78 is Normal. All but one of the samples are categorized as "Normal," and one sample is deemed "Good Looking," which has an even higher predicted score of 3.22. This means that the model actually find out more beautiful faces. Ultimately, the scores are pretty close to the max possible given an average beauty rating of 5 out of 10 for the model, meaning this one works, though there are differences in beauty ratings.

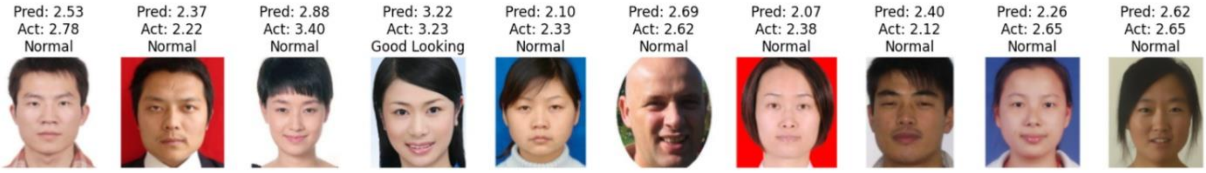

Figure 6. Sample Predictions

Table 1. Comparison of Various Studies on Facial Beauty Prediction

Study	Datasets	Models	Accuracy
Anderson et al. (2018)	Celeb A	ResNet50	**82.52%**
Gan et al. (2020)	SCUT-FBP5500	2M BeautyNet	**68.23%**
Dornaika et al. (2020)	SCUT-FBP5500	semi-supervised schemes	**86.60%**
Gan et al. (2023)	SCUT-FBP5500	EfficientNets-based transfer learning	**73.13%**

The differences between predicted and actual values are distributed as shown in Figure 5. In table 1, the comparison of various studies on facial beauty prediction illustrates useful findings about the performance of different models and datasets. For instance, Anderson et al. (2018) achieved an remarkable accuracy of 82.52%, using ResNet50 model on Celeb A dataset, which show the power of deep learning techniques. Meanwhile, the 2M BeautyNet model for SCUT-FBP5500 dataset from Gan et al. (2020) achieved an accuracy of just 68.23%, meaning there's still ground to be covered with that method. However, Dornaika et al. (2020) achieved impressive performance of 86.60% on the same SCUT-FBP5500 data set with semi-supervised approaches, showing the potential advantages of semi-supervised learning. Additionally, Gan et al. (2023) applied EfficientNets combined with transfer learning on the SCUT-FBP5500 dataset, achieving an acceptable accuracy of 73.13%. In general, these comparisons emphasize the limitations of several models and approaches for facial attractiveness classification.

D. Conclusion

Into conclusion after all artificial intelligence is able to measure these complex human beauty perceptions, understanding what makes a face beautiful in order to provide it with a facial beauty score. Our experimentation reflects that if we have the appropriate dataset and model configuration, we can get a high accuracy for beauty detection. Our success highly relies on a diverse frontal facial dataset such as SCUT-B 5500. This was a large enough dataset, allowing us to train the model on multiple features. Our research suggests that deep learning can greatly improve facial beauty score computation, and impact areas such as social media, advertisement, and personalized marketing and based on this information, insights can be drawn.

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