Facial Beauty Prediction Based on Vision Transformer

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***Abstract*—Facial beauty analysis is a crucial subject in human culture among researchers across various applications. Recent studies have utilized multidisciplinary approaches to examine the relationship between facial traits, age, emotions, and other factors. Facial beauty prediction is a significant visual recognition challenge that evaluates facial attractiveness for human perception. This task demands considerable effort due to the novelty of the field and the limited resources available, including a small database for facial beauty prediction. In this context, a deep learning method has recently shown remarkable capabilities in predicting facial beauty. Additionally, vision Transformers have recently been introduced as novel deep learning approaches and have shown strong performance in various applications. The key issue is that the vision transformer performs significantly worse than ResNet when trained on a small ImageNet database. In this paper, we propose to address the challenges of predicting facial beauty by utilizing vision transformers instead of relying on feature extraction based on Convolutional Neural Networks, which are commonly used in traditional methods. Moreover, we define and optimize a set of hyperparameters according to the SCUT-FBP5500 benchmark dataset. The model achieves a Pearson coefficient of 0.9534. Experimental results indicated that using this proposed network leads to better predicting facial beauty closer to human evaluation than conventional technology that provides facial beauty assessment.**

***Index Terms*—facial beauty prediction, vision transformer, deep learning, convolutional neural networks, performance evaluation**

I. Introduction

Given that facial attractiveness is a fundamental aspect of human nature, the human face plays a significant role in both our social interactions and the pursuit of beauty [1]. The need for cosmetic surgery has significantly increased recently, highlighting the importance of having a sophisticated understanding of beauty in medical contexts. However, the study of human physical beauty has a history spanning over 4,000 years, demonstrating the ongoing significance of the topic [2].

Facial beauty prediction has garnered increasing interest and attention from researchers in various fields, including psychology, computer science, and evolutionary biology [3, 4]. This interdisciplinary study aims to analyze and predict the attractiveness of human faces using data-driven methods and mathematical models that align with human assessments [5, 6]. These methods involve acquiring face data from public databases, internet resources, or photographs generated through software or digital cameras. The acquired face data then undergoes pre-processing to standardize them, which include rectification, noise removal, and landmark localization, face cropping, intensity and scale normalization, and size normalization. Once the face data is pre-processed, a beauty score database is constructed. This process involves gathering attractiveness scores from a large group of human raters and using statistical analysis to derive a proxy for the ground truth beauty scores. The goal is to create models that can accurately predict facial beauty based on these scores. These models can have practical applications in various industries, such as fashion and cosmetics, where understanding facial beauty preferences can help in product development and marketing strategies [7].

Advances in computerized facial beauty analysis, with an emphasis on data-driven research and the results of quantitative experiments provides a comprehensive overview of the key advances in computerized facial beauty analysis and the validation of standard rules in facial beauty analytics [8, 9]. Computer scientists have recently started actively participating in the field of facial beauty prediction, contributing with their expertise in data-driven methods and mathematical modeling [10]. These advancements have helped bridge the gap between traditional beauty analysis done in psychology and the emerging field of computer vision and machine learning.

With the use of deep learning techniques and convolutional neural networks, researchers have been able to analyze facial features and accurately predict facial beauty ratings [11, 12]. These advancements have helped overcome the challenges associated with facial beauty prediction, such as the lack of resources and the subjective nature of beauty [13, 14]. These advancements in deep learning and computer vision have allowed for the development of more robust and reliable prediction models, which can be applied to various industries, including cosmetics, fashion, and entertainment [15, 16].

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Furthermore, the power and versatility of these algorithms, particularly Convolutional Neural Networks (CNNs), have fueled the development of deep learning architecture [17].

Vision Transformer, or ViT [18], is the new state-of-the-art method for image classification. ViT was posted to the archive in October 2020 and officially published in 2021 on all the public datasets [19]. ViT outperforms RestNet by a slight margin, given that ViT has been pre-trained on a sufficiently large dataset. The goal of this paper is to provide an overview of deep learning techniques, specifically vision transformers, in the field of facial beauty prediction [20].

The contributions of this work are presented as follows:

- We propose ViT-FBP: vision transformer architecture for facial beauty prediction.
- Firstly, we tackle the difficulties of facial beauty prediction on a small dataset using a vision transformer as opposed to feature extraction based on CNN commonly used for facial beauty prediction methods.
- Our ViT-FBP model consistently outperforms all previously published approaches on different facial beauty prediction tasks.
- We present state-of-the-art results on SCUT-FBP5500 dataset for facial beauty prediction by using our face alignment system making our scripts and the method of preprocessed faces accessible to the public at (https://github.com/DjameleddineBoukhari/ViT-FBP)

This paper is organized as follows: Section II contains several pertinent researches on predicting facial attractiveness. The procedure for selecting the utilized architectures is described in Section III. The experimental findings and the evaluation performance using the SCUT-FBP5500 dataset are presented in Section IV.

II. Related Works

Deep learning is a subset of machine learning. It proved an efficient tool compared to the traditional methods, such as geometric and textural features. In FBP, deep features from an input image are extracted using deep convolutional neural networks. However, the comparison between machine learning and deep learning is how each technique and data are used. A short brief on facial beauty prediction methods based on deep learning, supervised learning, or semi-supervised learning

A. Supervised Learning

Geometric prior GPNet: Peng *et al.* [21] propose using a dual-branch structure and geometric regularization with a hybrid network named GPNet. The two branches that identify the model structure are a local CNN branch and a global Swin Transformer branch, both of which are multi-scale feature fusion modules. An ensemble DCNNs: Saeed *et al.* [22] propose an ensemble DCNN-based regression model with an architecture of two fine-tuned, well-known pre-trained CNNs, namely AlexNet and VGG16, plus one network built entirely from scratch. The CNN-ER: Bougourzi *et al.* [23] proposed an ensemble CNN with two branches, ResneXt-50 and Inception-v3, for face beauty estimation. This ensemble is trained with four loss functions (dynamic ParamSmoothL1, dynamic Huber, dynamic Tukey, and MSE). Thus, most work uses transfer learning for facial beauty perdition. In addition, several pre-trained CNN models show their accuracy for the beauty evaluation task. Because Convolutional Neural Networks (CNNs) include fully connected layers, they usually utilize an end-to-end model to complete a classification or regression task [24]. However, by removing the fully connected layers and keeping only the convolutional ones, we can extract deep features [25]. Convolutional, pooling, and fully connected layers are the standard components of a CNN. Convolutional layers constitute the fundamental components of a CNN [26].

Cao *et al.* [27] introduced a deeper network architecture using Residual-In-Residual (RIR) groups. The authors also presented a face beauty database, SCUT-FBP5500 [28], which consists of 5,500 facial images with annotations for beauty scores. Two evaluation protocols, 5-fold cross validation 80%-20% and 60%–40% split, were used to test the proposed architecture with three CNN architectures: Alexnet [29], Resnet-18 [30], and ResneXt-50 [30]. The combined spatial-wise and channel-wise attention mechanism was also introduced for better feature comprehension, resulting in improved feature comprehension and better performance for FBP. R3CNN proposed by *Lin* et al. [31] integrates relative ranking into regression to improve the performance of FBP. This architecture can be flexibly implemented using existing CNNs as a backbone network. The proposed architecture provides better results than SCUT-FBP [11] and SCUT-FBP5500 [28] datasets.

FSCLDE: Dornaika *et al.* [32] proposed an efficient deep discriminant embedding method. They introduced a cascaded feature extraction and selection architecture that can enhance noisy and weak descriptors, transforming them into robust ones. This structure allows the conversion of any linear approach into a deep variation. The rate classification (%) of face beauty achieved by a 1-NN classifier across various embedding spaces on three face beauty datasets: SCUT-FBP5500, SCUT-FBP, and M2B, use the evaluation protocol of 5-fold cross-validation.

B. Semi-Supervised Learning

MSMFME: Dornaika [33] proposed a multi-view semi-supervised technique that fuses various graphs to create a unifying flexible manifold embedding model, which has been trained and tested using fivefold cross-validation, where tests are conducted on the SCUT FBP-5500 dataset. NFME: Dornaika *et al.* [34] propose a graph-based semi-supervised facial beauty prediction. The proposed method, NFME, is based on texture and handles the scenario of real score propagation as they modify and kernelize an existing linear flexible manifold embedding technique. Performance of face beauty is achieved by NFME on three face beauty datasets, SCUT-

FBP5500, SCUT-FBP, and M2B, with an evaluation protocol of 5-fold cross-validation.

III. Methods

In this section, we initially provide an outline of the proposed architecture. A typical transformer makes use of the attention mechanism in neural networks. The attention mechanism was first proposed for the language translation problem [35]. Our proposed ViT-FBP architecture uses the core network following the ViT standard, with 8 layers of transformer blocks for fundamental feature extraction. If we add two fully connected layers, performance could be improved. As a result, the network's capacity has increased [36, 37].

A. Overview of FBP Vision Transformer

We apply data augmentation to images and create a layer that splits the image into patches. Then, encode the patches into the vector that stores image patches. The core network is consistent with or adopts the original ViT to create multiple layers of the transformer block, a data normalization layer, and a multi-head attention layer to skip connections of encoded patches, a data normalization layer, a multi-layer perceptron, and skip connections. Then, the regression token is used with an MLP head to extract features, which are then calculated by two fully connected layers (FC). Two linear layers in the MLP have a GELU activation function, as shown in Fig. 1.

The input image is transformed using a set of parameters called d, such as rotation angle and crop coordinates. Saving it directly becomes memory-inefficient since d varies for every image in every cycle. To solve this issue, in order to encode d, we just use one argument, $d_0 = E(d)$, where E(·) is the encoder shown in Fig. 1.

The multi-head attention consists of several self-attention blocks in order to capture as many complicated interactions as possible between the various items in the sequence. Essentially, we repeatedly use the cycle through the attention process [38]. With d_{model}-dimensional keys, values, and queries, many attention functions should be used instead of just one, and the attention function is carried out in parallel with each of the projected versions of queries, keys, and values. Each matrix is multiplied by a different weight matrix to create the mapping. The attention mechanism has the ability to concentrate on any object on the input image compared to Convolutional Neural Networks (CNNs), which use variable-size convolution kernels to scan across the different levels of the architecture; besides it functions inside a single network layer. Moreover, Tokenization occurs at the pixel level, as indicated in Fig. 1 below, meaning that each pixel in the grid cares about each other pixel. In order to fix this, the input image is divided into equal-sized square blocks, or image patches. Then, for later use and retrieval, each image patch is unrolled into a one-dimensional sequence (n×1) and given a positional embedding to a table.

The dense layer inside a fully connected layer consists of 2048 nodes, and the second dense layer inside a fully connected layer block consists of 1024 nodes.

For regression models, PC improvements do not only attach to the model structural design but also to the loss functions used. During training batches, the loss function computes the total error and uses back propagation to change the weights. To deal with different domains, several loss functions have been developed, some of which are derivations of already existing loss functions. The imbalances in the dataset are also taken into consideration by these loss functions. In the case of regression model of FBP, the default and the most frequently option is MSE.

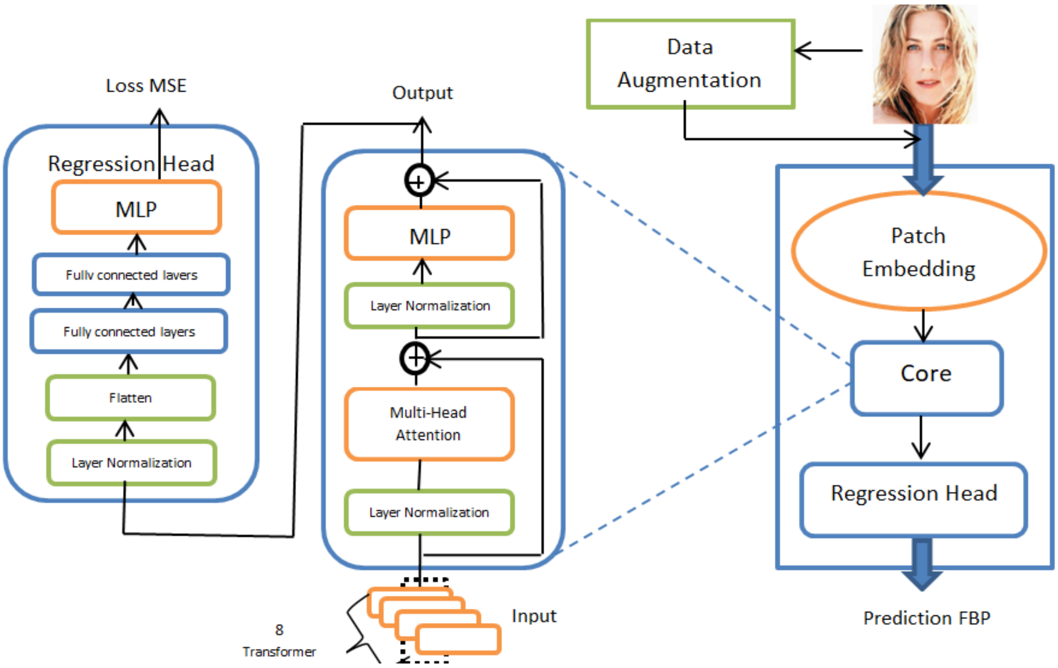


Fig. 1. Algorithm architecture, the core block consists transformer of an MHA, an MLP, skip connections, and layer normalizations.

IV. Experiments

The SCUT-FBP5500 dataset [28] is used for network training. Our network is trained for 600 iteration with batch size of b = 256. The Adam optimizer updates the parameters. The selected loss function was MSE.

A. The SCUT-FBP5500 Dataset

The SCUT-FBP5500 [28] data refers to a dataset specifically designed for Facial Beauty Prediction (FBP) tasks [39]. To address limitations of existing FBP datasets by offering more diversity in:

- Ethnicity: Includes Asian and Caucasian individuals.
- Gender: Includes male and female individuals.
- Age: Covers a range from 15 to 60 years old.
- Beauty Scores: Provides subjective human-rated beauty scores ranging from 1 (least beautiful) to 5 (most beautiful).

Data Composition:

- Size: 5,500 frontal face images.
- Subsets: Divided into four equal subsets based on ethnicity and gender:

2,000 Asian females (AF)
2,000 Asian males (AM)
750 Caucasian females (CF)
750 Caucasian males (CM)

Data Labels:

Each image comes with two types of labels:

- Beauty Score: Assigned by human evaluators on a scale of 1 to 5.
- 86 Facial Landmarks: Markings on key facial features like eyes, nose, mouth, and eyebrows [40].

As shown in Fig. 2, Female Asian samples Male Asian samples, Female Caucasian samples and Male Caucasian samples.

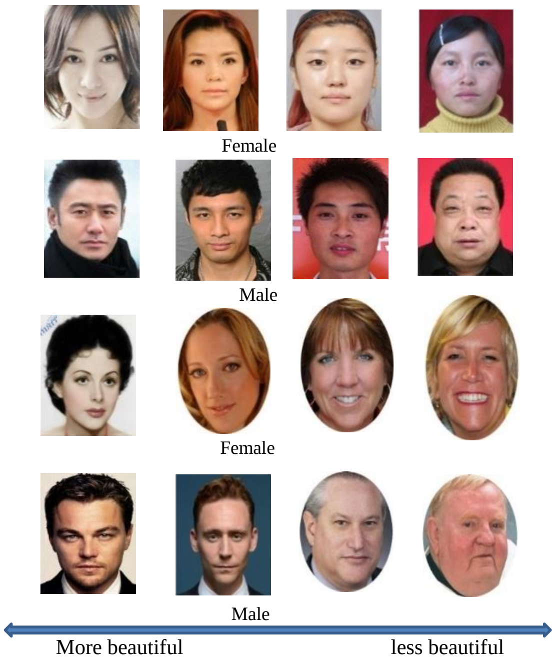


Fig. 2. Images of various facial features and beauty ratings from the SCUT-FBP5500 benchmark dataset.

B. Performance Evaluation

Depending on the application sought, the beauty prediction algorithm evaluated must be able to verify a certain number of prediction quality criteria, among which we can cite the Mean Absolute Error (MAE), the error Root Mean Square (RMSE), and the Pearson Correlation (PC) [41]. At this stage and after having obtained our prediction results, we must evaluate the performance of our system from the test data. And since the model belongs to regression problems, we will apply the specified metrics to this type of problem [42]. The metrics used are:

Mean Absolute Error (MAE) is defined by:

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}_i| \qquad (1)$$

Root Mean Squared Error (RMSE) is defined by:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}_i|^2} \qquad (2)$$

Pearson Correlation (PC) is defined by:

$$\mathrm{PC} = \frac{\sum_{i=1}^{N}(y_i - \bar{y_i})\,(\hat{y}_i - \bar{\hat{y}_i})}{\sqrt{\sum_{i=1}^{N}(y_i - \bar{y_i})^2}\,\sqrt{\sum_{i=1}^{N}(\hat{y}_i - \bar{\hat{y}_i})^2}} \qquad (3)$$

where y_i and $\hat{y}_i$ represent the ground truth label and prediction score of the ith image, and $\bar{y}$ and $\bar{\hat{y}}_i$ represent the average of all ground truth labels and prediction scores respectively. Higher PC and lower MAE and RMSE indicate better performance achieved by the FBP system [42, 43].

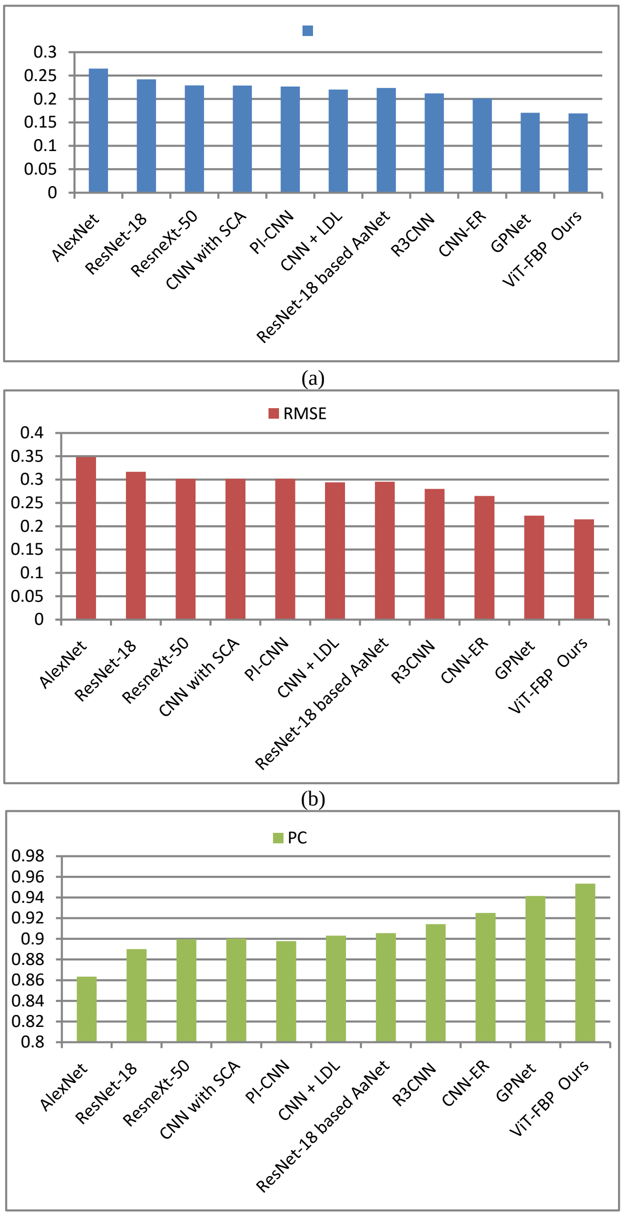
C. Compared with State-of-the-Art Methods

We conducted comparisons utilizing a range of techniques, including geometric feature-based and deep learning-based techniques, such as LR, GR, SVR, AlexNet, ResNet-18 and ResNeXt-50, etc. MAE, RMSE and PC are chosen as the metrics.

Five-fold cross-validation of facial beauty prediction is used to testify the network capacity via comparison, which holds 80% to 20% splitting for each fold in Table I and Fig. 3 show the comparison.

TABLE I: Performance Comparison of the Five-Fold cross Validation

Methods	**MAE**	**RMSE**	**PC**
AlexNet [26]	0.2651	0.3481	0.8634
ResNet-18 [27]	0.2419	0.3166	0.89
ResneXt-50 [27]	0.2291	0.3017	0.8997
CNN with SCA [24]	0.2287	0.3014	0.9003
PI-CNN [44]	0.2267	0.3016	0.8978
CNN + LDL [20]	0.2201	0.294	0.9031
ResNet-18 based AaNet [45]	0.2236	0.2954	0.9055
R3CNN [28]	0.212	0.28	0.9142
CNN-ER [20]	0.2009	0.265	0.925
GPNet [18]	0.1706	0.2225	0.9415
ViT-FBP Ours	0.1691	0.2149	0.9534



(a)

(b)

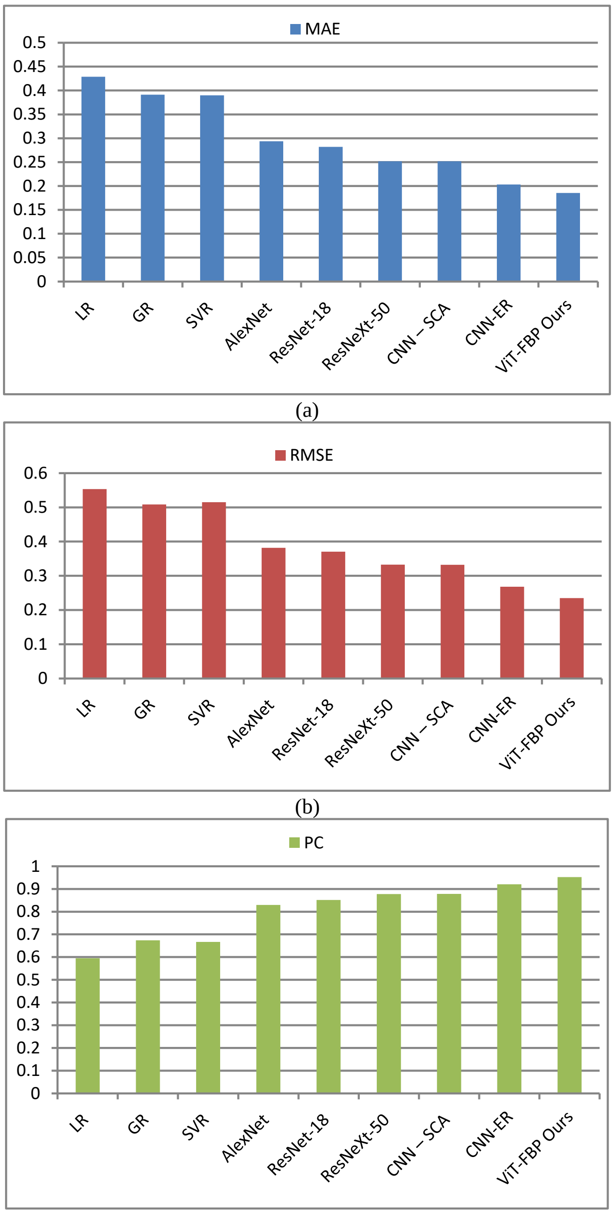
(c)

Fig. 3. Performance comparison of the five-fold cross validation, (a) Mean Absolute Error (MAE), (b) Root Mean Squared Error (RMSE) and (c) Pearson Correlation (PC).

For 0.6 of the dataset is used for training, while 0.4 is used for testing. This means, 40% of the data set's instances are randomly chosen for testing, while the remaining 60% are randomly picked for training in Table II and Fig. 4 show the comparison.

TABLE II: PERFORMANCE COMPARISON OF DIFFERENT METHODS BY 60–40% SPLITTING

Methods	MAE	RMSE	PC
LR [24]	0.4289	0.5531	0.5948
GR [24]	0.3914	0.5085	0.6738
SVR [24]	0.3898	0.5152	0.6668
AlexNet [26]	0.2938	0.3819	0.8298
ResNet-18[27]	0.2818	0.3703	0.8513
ResNeXt-50 [27]	0.2518	0.3325	0.8777
CNN – SCA [24]	0.2517	0.332	0.878
CNN-ER [20]	0.2032	0.2683	0.9207
ViT-FBP Ours	0.1854	0.2347	0.9519



(a)

(b)

(c)

Fig. 4. Performance comparison of different methods by 60–40% splitting, (a) Mean Absolute Error (MAE), (b) Root Mean Squared Error (RMSE) and (c) Pearson Correlation (PC).

D. Discussion

According to our study, most researchers prefer supervised pre-trained models over semi-supervised models or creating models from scratch. This is due to various reasons. Pre-trained models are typically quicker to train because they only require fine-tuning of hyperparameters. Additionally, pre-trained models require the modification of the output layer based on the task to generate the desired outputs. Performance enhancement is typically constrained by the number of parameters. Compared to other models such as AlexNet, ResNet-18, ResNeXt-50, CNN-SCA, and R3CNN, the suggested model demonstrates superior performance.

The VIT-FBP network has 82.62 million parameters. There are 6.75 million parameters in CNN-SCA. ResNeXt-50 has 25.03 million parameters, while AlexNet has 62.38 million parameters. Our network outperforms the referenced works, as indicated by the comparison. The abundance of parameters can be minimized through a well-designed Vision Transformer (ViT) procedure. The effectiveness of our suggested strategy is demonstrated by comparing the two situations using a five-fold cross-validation with an 80%–20% split. This suggests the superiority of the proposed ViT FBP Network over State-of-the-Art techniques.

Additionally, a pre-trained model has been utilized in recent supervised learning research. The model employs two branches, Inception-v3 and ResNeXt-50, with a dynamic loss function. Alternatively, three different DCNNs, including pre-trained VGG16, AlexNet, and simple CNNs, have also been implemented. Furthermore, geometrically regulated regression-based face landmarks utilize the PGNet model, which is a hybrid network consisting of a local CNN and a global Swin-Transformer structure. This model outperforms previous studies that utilized auxiliary tasks like gender recognition and race classification. The effectiveness of our proposed strategy is demonstrated through comparisons of the two scenarios using five cross-validation folds and a 60%–40% split. This supports the idea that both of the suggested ViT-FBP networks were essential in surpassing the most advanced techniques. However, this model calculates its parameters using data from face beauty scores falling within a specified range, as our aim is to predict the scores of facial beauty. It follows that the ground truth has the highest correlation with prediction values.

VIT-FBP has the potential to be used in a variety of applications, such as:

- Facial beauty assessment: VIT-FBP could be used to develop more objective and reliable methods for assessing facial beauty. This could be useful for applications such as matchmaking, beauty pageants, and product design.
- Facial editing: VIT-FBP could be used to develop more realistic and effective facial editing tools. This could be used to help people improve their appearance or to create more believable digital avatars.

Although facial beauty estimation is adaptable and could be approached as a regression, classification, or hybrid issue, most research approaches rely on a regression issue to obtain an accurate face beauty forecast.

E. Future Research

For more than a decade, convolutional neural networks have dominated computer vision research. Recent advancements in innovative topology, such as vision transformers, have demonstrated significant potential in enhancing the efficiency and performance of tasks like image segmentation, object identification, and classification. These models enable the modeling of long-range dependencies by combining the attention mechanism of Transformers with the effectiveness of convolutional neural networks. According to recent studies, the utilization of vision transformers for predicting facial beauty is a promising area for future research. The results are comparable to or even surpass those achieved using state-of-the-art deep convolutional neural network techniques. Furthermore, investigating the physiological reasons for facial preference, such as using fMRI to monitor brain activity during the perception of facial attractiveness or examining the impact of hormone levels on facial preference, can provide valuable insights into the underlying mechanisms of facial beauty perception.

3D face beauty prediction is another intriguing topic that warrants further investigation. Research on 3D photos is lacking, despite the effectiveness of deep convolutional neural networks in predicting face attractiveness for 2D images. Investigating the potential applications of 3D datasets for 3D facial plastic surgery and for predicting facial attractiveness in individuals from various ethnic backgrounds could lead to significant advancements in the industry. Nonetheless, there are still issues with using facial beauty technologies in industrial and medical contexts. Therefore, given the recent dramatic increase in demand for cosmetic surgery, understanding the concept of beauty is becoming increasingly important in medical settings.

V. Conclusion

Convolutional neural networks, a deep learning technique, have demonstrated promising outcomes in image processing, especially in facial beauty prediction. However, they continue to face several difficulties, such as the overfitting issue and the need for large datasets and powerful computing power.

In this paper, we propose ViT-FBP as a vision transformer framework for facial beauty prediction, regardless of whether deep networks have proven their effectiveness for such tasks. This framework has been successfully applied to various deep learning techniques. The results of the trial demonstrate that our network can outperform earlier CNN baseline techniques. According to the experimental findings, the suggested network outperformed several publicly available models, including AlexNet, ResNet-18, ResNeXt-50, CNN-SCA, and R3CNN. It enhances the evaluation of congruence with human judgment.

Overall, VIT-FBP is a promising new approach to predicting facial beauty. It is more accurate and interpretable than previous methods, and it has the potential to be used in a variety of applications.

Future research directions in the field of face beauty prediction utilizing a hybrid of Visual Transformers have made significant progress and shown promising results that either match or surpass the state-of-the-art deep convolutional neural network techniques on specific benchmarks. There are still several challenges associated with using facial recognition technologies in the medical field and business. Given the dramatic increase in demand for cosmetic surgery over the past few years, understanding beauty is becoming increasingly crucial in medical settings.

It is crucial to consider the diversity of raters, taking into account factors such as their age, gender, race, and ethnicity. This work provides a clear roadmap for future research in the area of predicting facial beauty by analyzing the state of the art in this field.

Conflict of Interests

The authors declare no conflict of interest.

Author Contributions

Djamel Eddine Boukhari; contribution was the proposition of the present method, design, and writing a draft of the manuscript, Ali Chemsa; formal analysis, interpretation, revision and proofreading, Riadh Ajgou; worked on Concepts, data analysis, and discussed the results; all authors had approved the final version.

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Data Availability Statement

The dataset SCUT-FBP5500 analyzed during the current study is available in the Github repository, https://github.com/HCIILAB/SCUT-FBP5500-Database-Release

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