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Hybrid Transfer Learning Model for Facial Attractiveness Prediction

Hawar Bahzad Ahmad[1,2], Adnan Mohsin Abdulazeez[3]
hawar.doski88@gmail.com [1],hawar.doski@nawroz.edu.krd[2],adnan.mohsin@dpu.edu.krd[3]
[1] IT Dept., Technical College of Informatics, Akre University for Applied Sciences, Duhok, Iraq.
[2] College of Science, Department of Computer Science, Nawroz University, Duhok, Kurdistan Region, Iraq.
[3] Technical College of Engineering, Duhok Polytechnic University, Duhok, Kurdistan Region, Iraq.

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Abstract

Prediction of facial attractiveness greatly depends on the subjective terminology applied according to the diverse cultural, social and psychological considerations. This task is important for applications in many fields, such as aesthetics, entertainment, wardrobe recommendations, etc., and requires accurate and robust models. Current methods predominantly adopt a single model, which is unable to learn the diverse attributes that can influence the quality of facial beauty. In order to overcome these challenges, this study proposes a hybrid transfer learning framework for feature extraction and prediction that combines ResNet50 and InceptionV3. In this methodology, Multi-task Cascaded Convolutional Networks (MTCNN) is used for accurate face detection and preprocessing, then features extraction is done using pretrained ResNet50 and InceptionV3 architectures. The features extracted are then normalized and fused together and passed through a dense classification layer with application of dropouts and regularization in order to make the model robust. The CelebA dataset was used to train the model, utilizing class weights to account for imbalanced data and callbacks to optimize performance. Test accuracy and F1 Score of the proposed model is found to be 83.58% and 0.8384 respectively, which shows good generalization on unseen data. The validation frames the performance of the hybrid framework which leverages the complementary strengths of multiple CNNs, and thus provides robust performance.

A. Introduction

Evaluating facial attractiveness is a multidimensional challenge that has attracted more and more attention in the fields of computer vision, psychology, and artificial intelligence research. Use of automatic facial attractiveness prediction may entail beauty evaluation, cosmetic recommendation, social media analysis as well as the aesthetic-driven AI systems [1], [2]. The perception of beauty is subjective, and the construction of attractiveness is influenced by multiple factors, including symmetry, proportions of the face, and cultural bias; thus, the prediction of facial attractiveness is a non-trivial task despite the advancements of deep learning in recent years [3].

Traditional techniques for predicting attractiveness used gestalt techniques, such as Hervé's approach, which uses hand-crafted features, ranging from facial geometry, symmetry analysis, and the golden ratio [4]. However, such approaches were only capable of detecting high level aesthetic pattern and not tailor made for different facial structure. The launch of deep learning, especially convolutional neural networks (CNNs), has completely transformed facial analysis by allowing automatic feature extraction and classification directly from raw photo knowledge [5], [6], [7]. Other research works have implemented CNNs architectures to map facial attractiveness predictors by using large-scale datasets SCUT-FBP5500 and CelebA [8], [9], [10]. Despite their promising results, some significant drawbacks still remain on the Framing of limited representation of features, data set imbalance, subjectivity in extracting attractiveness and high computational cost [11], [12], [13]. While deep learning-based approaches have achieved breakthroughs in this domain, most existing approaches use a single CNN for feature extraction, which might be insufficient to represent the wide range of facial attributes influencing the perceived attractiveness [5]. Furthermore, preprocessing methods like accurate MTCNN based face alignment and augmentation-based class balancing is still rarely used in facial attractiveness prediction [12], [14]. This emphasizes that it is still needed to be used hybrid feature extraction techniques using different deep learning architectures together to achieve prediction accuracy while identifying the relevant features which leads us to predict the desired output.

In this study, a hybrid transfer learning model combining ResNet50 and InceptionV3 to improve facial attractiveness prediction in features extraction and classification. The key aims of this study are:

- Combine the ResNet50 and InceptionV3 networks to exploit the capacity of their distinct feature extraction.
- Face Detection and Alignment: Perform face detection and alignment using MTCNN to ensure that all the inputs are consistent.
- Use data augmentation strategies to tackle class imbalance and apply such techniques to increase the generalization capability of the model.
- Assess model performance on CelebA dataset: accuracy, F1-score and AUC-ROC are performance metrics.

By addressing these objectives, the proposed approach contributes to improving classification accuracy, model generalization, and dataset fairness in deep learning models for facial attractiveness prediction. The findings of this study provide insights into the effectiveness of hybrid deep learning architectures and preprocessing techniques in enhancing classification performance.

The rest of the paper is organized as follows: Section B describes the proposed hybrid transfer learning model for facial attractiveness prediction. We highlight the motivation behind using ResNet50 and InceptionV3. Related Work reviews the state-of-the-art of facial aesthetics prediction and related deep learning techniques. The Methodology provides details on the three main components of the framework: MTCNN for face detection, two feature extraction techniques, and a classification pipeline. Under the Experiments and Results sub-section, the paper provides the training, fine-tuning and testing performance metrics (accuracy, F1 Score, etc. The Conclusion makes inferences regarding the results, such as issues on dataset diversity, overfitting, and future work towards fairness and generalization.

B. Related Work

Identification of facial attractiveness is a time-honored research topic in psychology and computer vision. It is a major advancement step in this field since the advent of deep learning which allows for the use of both trained neural spectra for aesthetics through feature extraction. "We were employing handcrafted features such as symmetry and proportions to predict attractiveness based on psychological studies that stated we preferred certain traits [8]", the researchers said. Data-driven approaches have been prevalent with the release of large-scale public datasets, such as SCUT-FBP and CelebA, which provide large-scale evaluation platforms for face beauty prediction models [9].

Feature extraction for predicting facial aesthetics is one of the key research areas. VGG16 and ResNet50 are examples of Convolutional Neural Networks (CNNs) that are widely used as base models in numerous studies. ResNet50 displays efficacy in capturing features hierarchically while addressing the problem of vanishing gradients using deep residual connections [5], [15]. Another popular model, InceptionV3, introduced the use of factorised convolutions, which yield computationally efficient networks with comparable performance [6], [16]. Both architectures were adapted to facial attractiveness prediction, exhibiting their versatility in extracting features from different datasets such as CelebA [3].

Further works also opened the field by introducing various different tools, such as Generative Adversarial Networks (GANs) into facial beauty research. BeautyGAN, BeautyGlow and other established models have the ability to edit images by translating beauty-related characteristics while preserving identity [17]. These and similar GAN-based approaches showcase the potential for combining aesthetic prediction and facial enhancement and beautification tasks. However, frequently these works are concerned with localized changes like make-up transfer, rather than a global notion of facial desirability [18].

Furthermore, multi-task learning has been successfully incorporated to enhance the prediction of attractiveness. Research has focused on integrating facial beauty prediction with auxiliary tasks like gender or age classification so that features such as texture, lighting, and skin tone can be exploited, leading to better model generalization [2]. This is in line with the established findings that demographic features such as gender and age play a significant role in perceptions of attractiveness and underscoring the importance of having a representative dataset [3], [8].

This field is still struggling with issues of diversity in datasets and biases in annotations. The CelebA and SCUT-FBP datasets, which are often used for the purpose, often show imbalanced demographics resulting in a biased prediction [3]. To mitigate these limitations, approaches like balanced sampling, attribute aware data augmentation, and domain adaptation have been investigated [2], [8]. These attempts are designed to make sure that models perform well for different ethnic groups, and for all different ages and all different expressions.

This is a technique that reveals the contribution of individual pixels in terms of model predictions, and papers using this method to validate predictive performance also abound in recent literature [2]. An alternative approach, specifically tailored toward identifying which features attract scores, can help develop a bridge between machine learning models and psychological models of beauty.

Most research on prediction of facial attractiveness focused on improved accuracy with inventive architectures and, efficient preprocessing techniques. Zhao et al. (2023), which focused on explainable deep learning frameworks for attractiveness evaluation, demonstrated the need for alignment between machine predictions and human perception [19]. A study by Kim et al. [20], (2022) provided a new technology of data augmentation to improve the generalizability of facial beauty model learned from a small dataset.

Chen et al. (2023) introduced a hybrid model that integrates CNN and graph-based models for contextual features in order to achieve better prediction ability [21]. Lee et al. In [22], the authors designed a lightweight neural network that runs on mobile platforms, achieving strong accuracy whilst optimising for performance. Lastly, Park et al. (2023), demonstrated the effect of various demographic datasets on model fairness and emphasized that a more comprehensive approach to datasets could help mitigate bias in model prediction of facial attractiveness [23].

C. Material and Methods

In this section, we will explain the suggested structure of facial attraction prediction, combining ResNet50 and InceptionV3 as characteristics extractors and training and testing with the CelebA dataset. The method consists of three main steps, face extraction, feature extraction, and classification. The model is reinforced with better accuracy using the Multi-task Cascaded Convolutional Networks (MTCNN) for precise image cropping and transfer learning implementations. Figure 1 presents the workflow of the proposed hybrid transfer learning model.

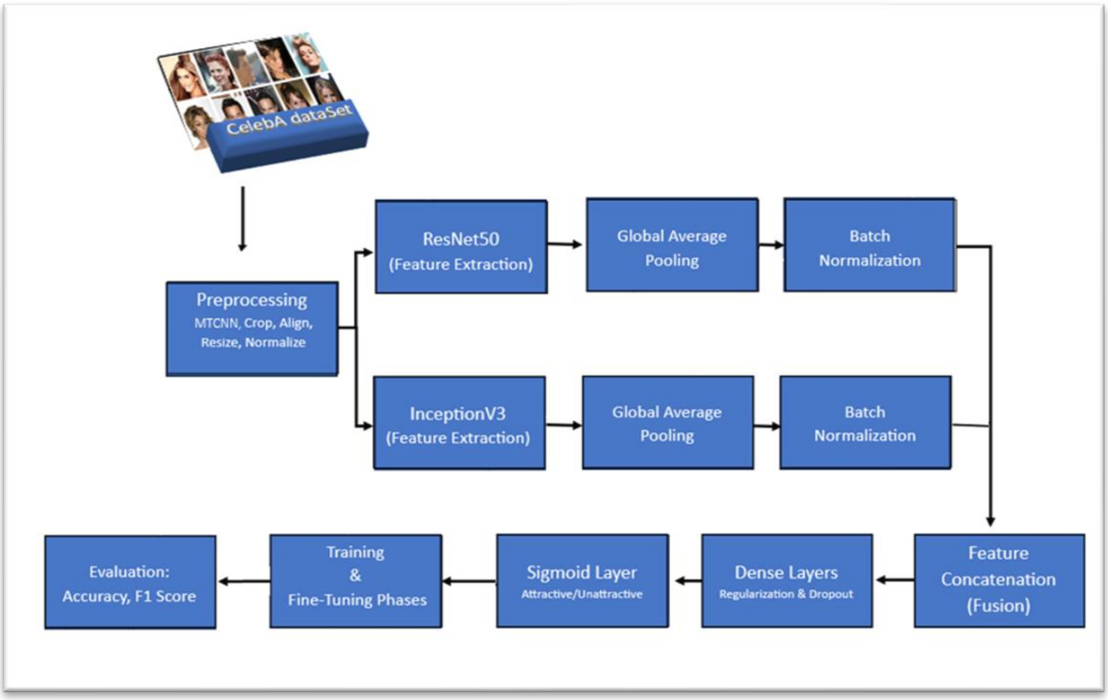

Figure 1. Hybrid Transfer Learning Workflow for Attractiveness Prediction

- **Preprocessing and Data Preparation**

The CelebA dataset, consisting of over 200,000 celebrity images with 40 annotated facial attributes, was used in this study [3]. To ensure a balanced classification and mitigate potential bias, a subset of 10,000 images was selected, maintaining an equal distribution of attractive and non-attractive faces. The preprocessing pipeline included face detection, resizing, normalization, class balancing, and dataset splitting, ensuring optimal input quality for training.

Representative samples from the CelebA dataset are shown in Figure 2. Standard frontal images with balanced lighting contrast with challenging cases affected by pose and illumination, underscoring the importance of robust preprocessing strategies.

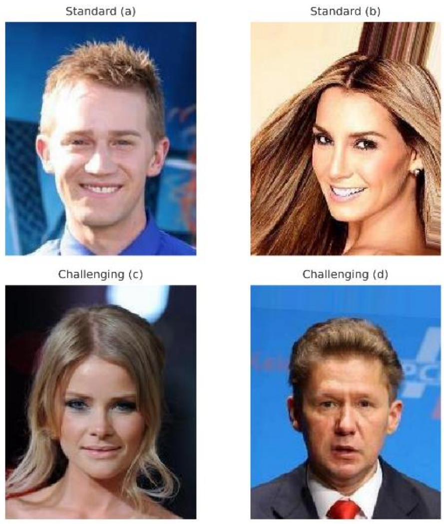

Figure 2. Representative samples from the CelebA dataset.
(a–b) Standard frontal cases; (c–d) challenging cases with pose and illumination variations.

- **Face Detection and Cropping**

To extract facial regions and ensure alignment, Multi-task Cascaded Convolutional Networks (MTCNN) [12] was used for face detection. MTCNN is a widely used deep learning-based face detector that simultaneously detects faces and key facial landmarks, ensuring proper alignment before feeding images into the model. Each detected face was cropped while preserving the original aspect ratio, eliminating background noise and non-facial elements.

However, the feature extraction process during face detection is not without challenges. Variations in image quality, such as low resolution or blurring, may introduce noise and obscure critical facial details. Illumination differences, including shadows or overexposed regions, can reduce the consistency of extracted features across samples. In addition, pose variations, such as tilted or non-frontal views, complicate landmark localization and alignment, potentially leading to incomplete or distorted feature representations. These challenges collectively influence the robustness and accuracy of the detection pipeline. To mitigate these issues, the preprocessing framework incorporated normalization procedures and augmentation strategies, ensuring that the extracted features remained reliable and suitable for subsequent learning tasks.

- **Image Resizing and Normalization**

After face detection, all images were resized to 350 × 350 pixels to ensure compatibility with both ResNet50 and InceptionV3, which require fixed input dimensions [5], [6]. To enhance training stability, pixel values were normalized to a range of [0,1] by dividing by 255, ensuring that feature learning occurs within an optimal numerical range [1].

- **Handling Class Imbalance**

Facial attractiveness datasets often suffer from class imbalance, where certain attractiveness labels (e.g., “attractive”) are underrepresented [11]. To address this limitation, targeted data augmentation techniques were applied to the minority class. The augmentation process involved random rotations of up to ±20° to account for head tilts, horizontal flipping to improve robustness against mirrored orientations, and brightness adjustments within a ±20% range to simulate varying lighting conditions. These operations increased the diversity of the training data while preserving the semantic integrity of facial features, thereby ensuring that the model generalized effectively to unseen samples [8].

- **Train-Test-Validation Splitting**

The dataset was partitioned into training, validation, and testing subsets to facilitate model learning and evaluation. Specifically, 70% of the data was allocated for training, 15% for validation during hyperparameter tuning and early stopping, and the remaining 15% for final testing. To ensure a fair and balanced evaluation process, the split was performed in a stratified manner, maintaining equal representation of both attractive and non-attractive classes across all subsets [24].

- **Feature Extraction**

The foundation of the proposed framework consists of the ResNet50 and InceptionV3 state-of-the-art CNN architectures, which have been pretrained on ImageNet. These are used as feature extractors using transfer learning to capture high-level and fine-grained features of the face.

- ResNet50: ResNet50's residual connections mitigate the vanishing gradient problem, enabling effective learning in deep networks. Its ability to extract diverse features from complex datasets like CelebA makes it ideal for attractiveness prediction [5]. Figure 3 highlights the hierarchical structure of ResNet-50, which extracts high-level features crucial for facial attractiveness prediction.

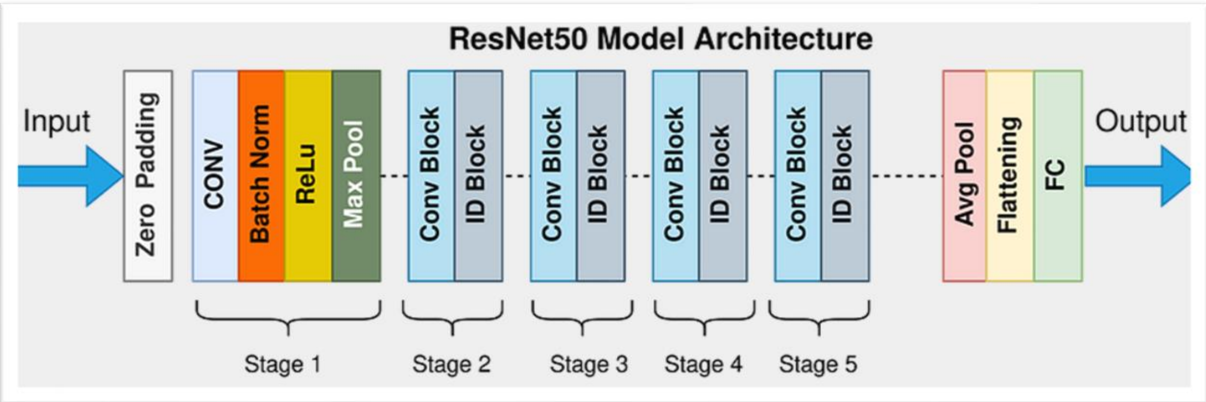

Figure 3. Resnet-50 Model architecture [25]

- InceptionV3: Due to the fact that it uses factorized convolutions, InceptionV3 captures multi-scale information by employing convolutional filters of various sizes. It is designed in such a way that it has less computational complexities and achieves excellent performance, especially in image classification [6]. As an example, figure 4 shows the modular nature of Inception V3, containing the inception modules, factorized convolutions, and other features

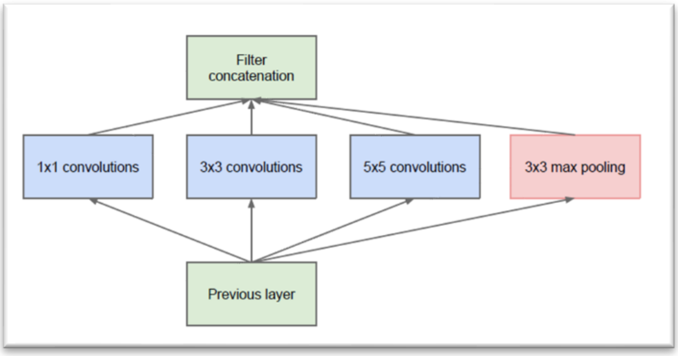

Figure 4. Inception V3 Model Architecture [26]

Output from the second to final layer of each model (a 2048-dimensional feature vector) is used as input for the classification model. These feature vectors all embodiments of high-level representations of facial attributes and intimacy.

- **Classification**

ResNet50 and InceptionV3 features are passed to a dense layer then a softmax layer, for classifying the faces into two classes (attractive or unattractive). The classification network consists:

- Dense Layer: To minimize the feature vector size without losing information. Figure 5 depicts the structure of the dense layer, which is employed to refine feature vectors for binary classification.

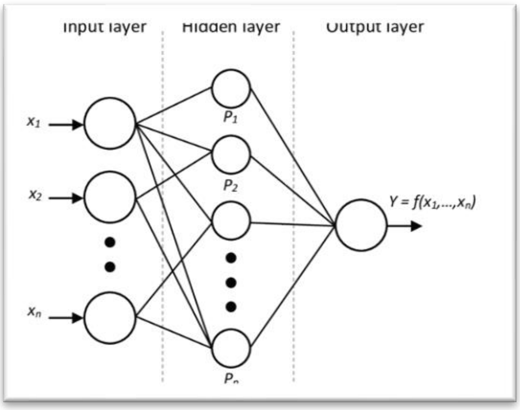

Figure 5. Dense Layer Architecture for Classification [27]

- Softmax Activation: Apply to Compress Feature Vector without losing Information The dense layer structure, which is used to improve feature vectors for binary classification, is depicted in Figure 5.

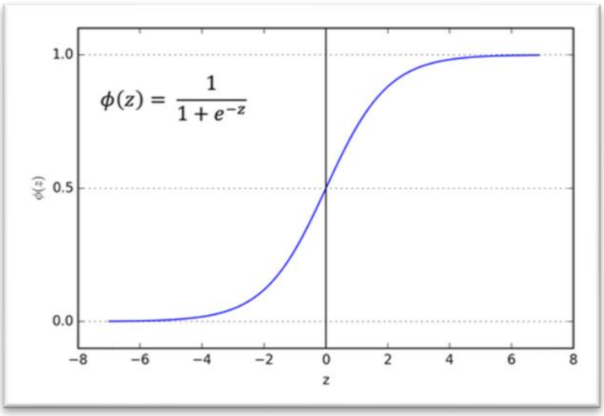

Figure 6. Binary classification with Softmax

We used the Adam optimizer with a learning rate of 4×10^{-4} and the categorical cross-entropy loss function to tune the network. The model was trained for 50 epochs using a batch size of 32 with early stopping to prevent overfitting.

- **Evaluation Metrics**

The following metrics were used to evaluate the models:

- Accuracy: Measures the accuracy of the number of correctly classified images.

$$\text{Accuracy} = \left(\frac{Correcr\ Predictions}{Total\ Cases}\right) \times 100\%$$

- F1-Score: Evaluate the model performance based on true positives and false positives.

$$\textbf{F1-Score} = 2 \times \frac{Precision \times \text{Recall}}{Precision + \text{Recal}}$$

- Area Under the Receiver Operating Characteristic Curve (AUC-ROC): The AUC-ROC measures how well the model distinguishes between the two classes.

$$\text{AUC-ROC} = \int_0^1 TPR(FPR)\, d(FPR)$$

D. Experiments and Results

The experiments were conducted on Google Colab, which provided GPU acceleration to facilitate model training and fine-tuning. This configuration ensured efficient execution and supports the reproducibility of the reported results.

- **Training and Fine-Tuning**

In the first phase, the proposed model was trained and fine-tuned. The first training period served to adapt the final dense and softmax layers of pretrained ResNet50 and InceptionV3 feature extractors to the facial attractiveness classification task. The learning rate was set to 4×10^{-4} for 40 epochs, followed by unfreezing the base layers of the feature extractor, and employing further fine-tuning using a lower learning rate of $4\times10^{-5}$for another 10 epochs.

The training process showed consistent improvement in both accuracy and loss:

- Final Training Accuracy: 93.46%
- Final Training Loss: 0.2845
- Validation Accuracy: 84.57%
- Validation Loss: 0.6508

The low gap between training and validation metrics demonstrates that the model is learning efficiently with minimal overfit, thereby attesting to the strength of the new transfer learning framework.

- **Testing Results**

The model was then evaluated for generalization performance on a held-out test set, with results summarized below:

- Test Accuracy: 83.58%
- Test Loss: 0.4481
- F1 Score: 0.8384
- (AUC-ROC): 0.86

These results show a clear, strong performance given the balanced F1 Score but also the AUC-ROC highlighting that the model properly accounts for class imbalance as well as class separation capabilities for reliable results. The relative low-test loss further indicates the model generalizes well to previously unseen data, so that the preprocessing, training, and hybrid transfer learning methodologies used are balanced.

- **Performance Analysis**

- Training Phase: During this phase, we can see training Acc (93.46%) and training loss (0.2845), which indicates that the model has learned about the relevant features in the train set, since we are using the pretrained weights of ResNet50 and InceptionV3.
- Validation Phase: The model reaches a validation accuracy of 84.57% and a loss of 0.6508, which indicates that underfitting and overfitting are well-balanced. The small difference between training and validation accuracy (8.8%) suggests strong generalization during training.
- Test Phase: The test metrics (accuracy = 83.58% and loss =0.4481) are in good agreement with validation metrics, indicating that model has performed consistently over the train, val and test dataset splits.

- **Comparison with Existing Studies**

To put the performance of the proposed model into context, a comparison was made to other works that use the CelebA dataset for facial attractiveness classification. The results of these studies are summarized in table X, illustrating the performance metrics of the various methodologies.

Table 1. Comparison of Facial Attractiveness Models on CelebA

Reference	Problem Type	Dataset	Gender	Performance
[9]	Classification	CelebA	F/M	ACC. 82.5%
[24]	Classification	CelebA	F/M	F1-Score 81.8%
[28]	Classification	CelebA	F/M	ACC. 82.8%
[29]	Classification	CelebA	F/M	ResNet50 with Loose-Crop: ACC. 82.52%, F1-Score 83.51%
This Study	Classification	CelebA	F/M	ACC. 83.58%, F1-Score 83.84%

This comparison shows that the performance of different methods continue to improve over time. Example, ResNet50 as feature extractor only gives 82.5% accuracy. In a similar manner [25] showed an 82.8% accuracy reaching slightly higher results than [9]. An important progress was obtained in [26], which uses loose-crop preprocessing with ResNet50, giving rise to 82.52% accuracy and F1 Score of 83.51%. This indicates the effect of preprocessing methods on predicting model performance as illustrated in table 1.

In contrast, the hybrid transfer learning model proposed in this study comprehensively outperformed all former methods, with the highest test accuracy (83.58%) and F1 Score (0.8384). By combining ResNet50 and InceptionV3, the model could take advantage of different feature extraction processes, enhancing its capacity to separate those features that make a difference for determining attractiveness. In addition, balanced class weights and fine-tuning contributed to improve the model's generalization on unseen data.

E. Conclusion

In this study, we proposed a facial attractiveness prediction framework based on transfer learning methods using ResNet50 and InceptionV3 on CelebA dataset. With a test accuracy of 83.58% and an F1 Score of 0.8384, the model is shown to generalize well across unseen data. However, fine-tuning improved the performance of the model by allowing deeper feature extraction, while the classification pipeline effectively balanced precision and recall. These findings validate the potential of the methodology for real-world applications, including aesthetic analysis and personalized recommendation systems.

However, it also notes areas in which it can improve — like addressing issues of overfitting and making the dataset more diverse with additional demographic categories such as ethnicity, gender, and sexual orientation. These improvements may help model robustness and fairness. Future lines of work could also involve multi-task learning and explainability techniques that allow the computational predictions to be better aligned with psychological theories, providing a more interpretable and inclusive methodology for the assessment of facial attractiveness.

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