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Synthetic Facial Aging: A Comparative Study of Stable Diffusion and StyleGAN

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Abstract. This study evaluates and compare two identity-preserving facial aging models: **FADING (Stable Diffusion)** and **SAM (StyleGAN)**. Using a balanced dataset by ethnicity and gender, we generated transformations across five target ages (30–70 years) and assessed identity similarity via ArcFace and demographic bias. Results show that **FADING reliably preserves identity**, particularly for Black and Indian females, while SAM exhibits variable performance and decreased consistency in older age groups and non-White subjects. FADING also produces high-fidelity, biologically plausible aging. These findings demonstrate the robustness of diffusion-based approaches for applications such as forensic search, long-term identity verification, and digital aging, highlighting the need for fairness-aware evaluation in facial aging models

Keywords: Stable Diffusion, GAN, StyleGAN, Identity Preservation, Facial Aging

1 Introduction

The 2024 Brazilian Public Security Yearbook Fórum Brasileiro de Segurança Pública [1] highlights the rising number of missing persons in Brazil, with cases increasing from 77,823 in 2022 to 80,317 in 2023—averaging 220 cases per day. Most cases occur in the Southeast region, which accounts for 42% of the national total. In addition to the high incidence, challenges in recognizing missing persons are further compounded by natural age-related changes, particularly in cases involving young children or those missing for extended periods. Advancements in artificial intelligence, particularly in face generation with models like Generative Adversarial Networks (GANs) [2] and Stable Diffusion [3, 4], offer potential solutions for simulating facial aging. Although GANs are capable of producing realistic images, they often face limitations such as instability during training and mode collapse. In contrast, Stable Diffusion has demonstrated the ability to generate highly detailed, identity-preserving images that effectively simulate the gradual aging process.

2 Background

In recent years, the field of image synthesis has experienced rapid progress, particularly in the domain of facial image manipulation. Techniques such as Generative Adversarial Networks (GANs) and diffusion-based models have demonstrated remarkable capabilities in generating high-quality, realistic images. These advancements have been especially impactful in facial aging applications, where maintaining identity consistency while accurately modeling age-related changes is critical.

This section provides a brief overview of two foundational approaches that have shaped the development of facial aging models: Generative Adversarial Networks (GANs) and the Stable Diffusion architecture. Each method brings unique strengths and mechanisms for generating photo-realistic faces, offering complementary insights into the state-of-the-art in facial image synthesis.

2.1 GANs

Generative Adversarial Networks (GANs) have significantly influenced the field of facial aging, providing high-fidelity image synthesis capabilities. These models consist of two competing neural networks: a generator,

which produces synthetic images, and a discriminator, which evaluates their authenticity [2]. Through adversarial training, GANs improve their ability to generate realistic age-progressed faces while maintaining key identity features. Conditional GANs [5] extend traditional GANs by guiding generation with external labels, enabling controlled outputs such as facial aging. On the other hand, StyleGAN [6] uses style vectors to control fine image features, achieving high-resolution, attribute-controlled facial synthesis.

2.2 Stable Diffusion

The Stable Diffusion architecture marks a substantial leap forward in image generation by leveraging latent diffusion models to generate high-quality images in a controlled, computationally efficient manner [3, 4]. Rooted in the principles of denoising diffusion probabilistic models (DDPM) [4], the Stable Diffusion architecture utilizes a latent representation that effectively captures the semantic characteristics of images while reducing the computational complexity typical of diffusion models operating in pixel space.

3 Methodology

This section outlines the methodological framework used to evaluate the performance of facial aging models across various demographic subgroups. The process includes data preparation, synthetic age progression, and comparative evaluation of two state-of-the-art generative models - FADING [7] and SAM [8]. The methodology emphasizes demographic diversity, systematic age progression, and rigorous assessment through quantitative identity metrics and visual inspection. It also incorporates a bias analysis component to assess the fairness and generalizability of the models across ethnicity and gender. The subsections below detail the dataset preparation, image transformation pipeline, model comparison, and the evaluation metrics employed.

3.1 Dataset Preparation

The proposed methodology begins with preparing a high-resolution dataset, which is crucial for evaluating facial aging models. To ensure diversity and representativeness, the following datasets have been selected: FFHQ [6], BUPT-CBFace [9], and LFW [10], ensuring balance across ethnicities and genders.

3.2 Aging Pipeline

To select the images used for modeling facial aging, the DeepFace framework was employed to identify young adults between 20 and 30 years old and verify ethnicity. The methodology involved three main steps. First, twenty young adult images from the FFHQ dataset [6] were selected for each ethnicity-gender combination (White, Black, Indian, and Asian; male and female), totaling 160 images and ensuring demographic diversity. Second, synthetic age transformations of these images were generated using two models: FADING [7] and SAM [8]. Each image was aged to five target ages: 30, 40, 50, 60, and 70 years, resulting in 1,600 synthetic images (800 per model). Third, the final dataset included the 160 original images and 840 real face images sampled from the LFW [10] and BUPT-CBFace [9] datasets, balanced by ethnicity and gender. The 1,600 synthetic images were then compared with this real dataset, providing a demographically balanced and representative evaluation of models performance.

3.3 Comparison of FADING and SAM

To evaluate the effectiveness of facial aging models, this study compares FADING [7] and SAM [8]. FADING employs a diffusion-based editing approach that enables high-fidelity image transformations while preserving critical identity features. In contrast, SAM adopts a style-based generative architecture, which allows for fine control over facial attributes but may introduce inconsistencies in identity preservation. The evaluation focuses on three main criteria: (i) identity preservation, assessing how accurately each method retains the subject's identity across different stages of aging; (ii) bias analysis, examining how each model performs across different ethnic groups to identify potential demographic biases; and (iii) visual realism, evaluating the perceptual quality of the aged faces using human-centered metrics. This process aims to ensure a representative and balanced evaluation framework for facial aging models, promoting fairness and improving predictive performance across diverse populations.

3.4 Evaluation Metrics

In this study, the ArcFace model [11] was selected within the DeepFace framework [12, 13] to evaluate identity preservation, due to its high performance and robustness in face verification tasks. The assessment involved computing similarity scores between original and aged images to quantitatively measure how well individual identities were retained across different stages of facial aging. This process was applied to the complete dataset of 840 images, performing a 1:N identity verification comparison.Based on these outcomes, we computed the following standard classification metrics: Precision, Recall, F1-Score and Accuracy. All metrics are reported with four decimal places to ensure analytical precision and allow for detailed comparison between models and demographic subgroups.

3.5 Identity Preservation and Bias Analysis

To provide a precise evaluation of identity preservation, we analyzed classification metrics - Precision, Recall, F1-Score, and Accuracy - for each gender and ethnicity combination, based on the updated results from the FADING and SAM models.

For White males, FADING achieved nearly perfect performance in younger age groups, with a reduction in Recall at 70 y/o (Recall = 0.1500), resulting in a total F1-Score of 0.7654. SAM showed comparable Precision in some age groups but considerably lower Recall in older ages, indicating reduced sensitivity and a total F1-Score of 0.6069. Among White females, FADING maintained good performance, achieving a total Recall of 0.6900 and F1-Score of 0.8166, while SAM had a total F1-Score of 0.6928, showing slightly lower consistency, particularly in older age groups.

Table 1. Age-Wise Evaluation of FADING and SAM Models on Identity Preservation for White Males

Metric	FADING						SAM					
	30 y/o	40 y/o	50 y/o	60 y/o	70 y/o	Total	30 y/o	40 y/o	50 y/o	60 y/o	70 y/o	Total
Precision	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.0000	0.9778
Accuracy	1.0000	0.9967	0.9922	0.9878	0.9811	0.9916	0.9989	0.9956	0.9856	0.9800	0.9767	0.9873
Recall	1.0000	0.8500	0.6500	0.4500	0.1500	0.6200	0.9500	0.8000	0.3500	0.1000	0.0000	0.4400
F1-Score	1.0000	0.9189	0.7879	0.6207	0.2609	0.7654	0.9744	0.8889	0.5185	0.1818	0.0000	0.6069

Table 2. Age-Wise Evaluation of FADING and SAM Models on Identity Preservation for White Females

Metric	FADING						SAM					
	30 y/o	40 y/o	50 y/o	60 y/o	70 y/o	Total	30 y/o	40 y/o	50 y/o	60 y/o	70 y/o	Total
Precision	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Accuracy	1.0000	0.9978	0.9956	0.9900	0.9822	0.9931	1.0000	0.9989	0.9867	0.9822	0.9800	0.9896
Recall	1.0000	0.9000	0.8000	0.5500	0.2000	0.6900	1.0000	0.9500	0.4000	0.2000	0.1000	0.5300
F1-Score	1.0000	0.9474	0.8889	0.7097	0.3333	0.8166	1.0000	0.9744	0.5714	0.3333	0.1818	0.6928

For Black males, FADING demonstrated good performance, achieving a total F1-Score of 0.7261 and Recall of 0.5816. SAM showed slightly lower results, with a total F1-Score of 0.6755 and Recall of 0.5100, particularly declining in older age ranges, indicating a modest increase in identity loss.

Among Black females, FADING clearly outperformed SAM, with a total F1-Score of 0.8256 and Recall of 0.7100, compared to SAM's 0.6164 F1-Score and 0.4455 Recall, showing a pronounced advantage and higher consistency across ages.

Table 3. Age-Wise Evaluation of FADING and SAM Models on Identity Preservation for Black Males

Metric	FADING						SAM					
	30 y/o	40 y/o	50 y/o	60 y/o	70 y/o	Total	30 y/o	40 y/o	50 y/o	60 y/o	70 y/o	Total
Precision	1.0000	1.0000	1.0000	1.0000	0.3333	0.9661	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Accuracy	1.0000	0.9956	0.9922	0.9856	0.9788	0.9904	1.0000	0.9933	0.9900	0.9822	0.9800	0.9891
Recall	1.0000	0.8000	0.6500	0.3500	0.0556	0.5816	1.0000	0.7000	0.5500	0.2000	0.1000	0.5100
F1-Score	1.0000	0.8889	0.7879	0.5185	0.0952	0.7261	1.0000	0.8235	0.7097	0.3333	0.1818	0.6755

Table 4. Age-Wise Evaluation of FADING and SAM Models on Identity Preservation for Black Females

Metric	FADING						SAM					
	30 y/o	40 y/o	50 y/o	60 y/o	70 y/o	Total	30 y/o	40 y/o	50 y/o	60 y/o	70 y/o	Total
Precision	0.9524	1.0000	1.0000	1.0000	1.0000	0.9861	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Accuracy	0.9989	1.0000	0.9967	0.9889	0.9822	0.9933	0.9967	0.9933	0.9791	0.9822	0.9811	0.9865
Recall	1.0000	1.0000	0.8500	0.5000	0.2000	0.7100	0.8500	0.7000	0.3667	0.2000	0.1500	0.4455
F1-Score	0.9756	1.0000	0.9189	0.6667	0.3333	0.8256	0.9189	0.8235	0.5366	0.3333	0.2609	0.6164

In the Asian male subgroup, FADING showed moderate to good performance, with a total F1-Score of 0.6351 and Recall of 0.4700, while SAM exhibited similar results, with a total F1-Score of 0.6207 and Recall of 0.4500, although performance declined notably in older age groups.

For Asian females, FADING achieved higher performance, with a total F1-Score of 0.7500 and Recall of 0.6000. In contrast, SAM performed worse overall (total F1-Score = 0.6928, Recall = 0.5300), indicating greater susceptibility to identity drift in this subgroup.

Table 5. Age-Wise Evaluation of FADING and SAM Models on Identity Preservation for Asian Males

Metric	FADING						SAM					
	30 y/o	40 y/o	50 y/o	60 y/o	70 y/o	Total	30 y/o	40 y/o	50 y/o	60 y/o	70 y/o	Total
Precision	1.0000	1.0000	1.0000	1.0000	0.8000	0.9792	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Accuracy	1.0000	0.9933	0.9833	0.9822	0.9811	0.9880	0.9989	0.9967	0.9856	0.9789	0.9789	0.9878
Recall	1.0000	0.7000	0.2500	0.2000	0.2000	0.4700	0.9500	0.8500	0.3500	0.0500	0.0500	0.4500
F1-Score	1.0000	0.8235	0.4000	0.3333	0.3200	0.6351	0.9744	0.9189	0.5185	0.0952	0.0952	0.6207

Table 6. Age-Wise Evaluation of FADING and SAM Models on Identity Preservation for Asian Females

Metric	FADING						SAM					
	30 y/o	40 y/o	50 y/o	60 y/o	70 y/o	Total	30 y/o	40 y/o	50 y/o	60 y/o	70 y/o	Total
Precision	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Accuracy	1.0000	0.9978	0.9911	0.9878	0.9789	0.9911	1.0000	0.9967	0.9889	0.9833	0.9789	0.9896
Recall	1.0000	0.9000	0.6000	0.4500	0.0500	0.6000	1.0000	0.8500	0.5000	0.2500	0.0500	0.5300
F1-Score	1.0000	0.9474	0.7500	0.6207	0.0952	0.7500	1.0000	0.9189	0.6667	0.4000	0.0952	0.6928

For Indian males, FADING maintained good performance across all age groups, achieving a total F1-Score of 0.6533 and Recall of 0.4900. SAM performed slightly worse, with a total F1-Score of 0.5816 and Recall of 0.4100, showing a modest gap and some decline in older age groups.

Among Indian females, FADING clearly outperformed SAM, achieving a total F1-Score of 0.8764 and Recall of 0.7800, compared to SAM's 0.6928 F1-Score and 0.5300 Recall, demonstrating a pronounced advantage and more consistent results across ages.

Overall, the results indicate that **FADING generally preserves identity more consistently across different ethnicities, genders, and age groups**, though the advantage varies by subgroup. **The most pronounced improvements were observed among Indian and Black females, particularly in older age groups**, while **performance between FADING and SAM was largely comparable for Asian and Indian males**. SAM tends to exhibit greater variability, particularly in older age stages, reflecting a higher susceptibility to identity drift in some subgroups.

Table 7. Age-Wise Evaluation of FADING and SAM Models on Identity Preservation for Indian Males

Metric	FADING						SAM					
	30 y/o	40 y/o	50 y/o	60 y/o	70 y/o	Total	30 y/o	40 y/o	50 y/o	60 y/o	70 y/o	Total
Precision	1.0000	1.0000	1.0000	0.7500	1.0000	0.9800	1.0000	1.0000	1.0000	1.0000	0.0000	1.0000
Accuracy	1.0000	0.9944	0.9878	0.9800	0.9800	0.9884	0.9956	0.9922	0.9878	0.9811	0.9778	0.9869
Recall	1.0000	0.7500	0.4500	0.1500	0.1000	0.4900	0.8000	0.6500	0.4500	0.1500	0.0000	0.4100
F1-Score	1.0000	0.8571	0.6207	0.2500	0.1818	0.6533	0.8889	0.7879	0.6207	0.2609	0.0000	0.5816

Table 8. Age-Wise Evaluation of FADING and SAM Models on Identity Preservation for Indian Females

Metric	FADING						SAM					
	30 y/o	40 y/o	50 y/o	60 y/o	70 y/o	Total	30 y/o	40 y/o	50 y/o	60 y/o	70 y/o	Total
Precision	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Accuracy	1.0000	0.9989	0.9956	0.9944	0.9867	0.9951	0.9989	0.9956	0.9922	0.9822	0.9789	0.9896
Recall	1.0000	0.9500	0.8000	0.7500	0.4000	0.7800	0.9500	0.8000	0.6500	0.2000	0.0500	0.5300
F1-Score	1.0000	0.9744	0.8889	0.8571	0.5714	0.8764	0.9744	0.8889	0.7879	0.3333	0.0952	0.6928

3.6 Visual Realism

To complement the quantitative metrics presented in the previous section, a qualitative visual analysis was conducted by the authors on representative samples of each demographic group: White Male, Black Male, Asian Male, Indian Male, White Female, Black Female, Asian Female, and Indian Female. This analysis focused specifically on the age stages of 60 and 70 years, as these were identified in the quantitative evaluation as the most distortion-prone intervals. It is important to note that this assessment was performed exclusively by the authors, without the involvement of external evaluators or crowd-based perceptual scoring.

For the **White Male** subject, both FADING and SAM demonstrated visually convincing aging effects, maintaining a coherent progression of facial features. FADING generated detailed and biologically plausible transformations, though at age 70, the wrinkles and skin texture became slightly overemphasized, producing a more severe appearance. SAM produced smoother results with consistent illumination but slightly reduced facial definition in comparison to FADING.

In the **Black Male** case, FADING preserved facial structure and key identity markers effectively, though minor darkening and contrast amplification were visible at older ages, particularly at 70 years. SAM maintained tonal uniformity but introduced subtle blurring around facial contours, which reduced the perceived sharpness of the identity. Overall, both models retained recognizability, with FADING showing more natural transitions.

For the **Asian Male** example, both models performed well, maintaining symmetry, geometry, and expression. FADING applied aging marks with moderate intensity, while SAM tended to produce smoother skin and slightly lighter tones at 70 years. Neither model introduced major artifacts, and both generated coherent visual progressions aligned with biological plausibility.

In the **Indian Male** example, FADING preserved identity features such as facial hair density and bone structure across both stages, although aging intensity increased noticeably at 70 years, resulting in slightly exaggerated texture effects. SAM produced cleaner but less detailed outcomes, with minor flattening of facial relief. Overall, both models maintained consistency, but FADING showed stronger realism.

For the **White Female** subject, FADING produced a clear aging progression, introducing wrinkles and graying hair naturally while preserving facial proportions. However, the 70-year output displayed a somewhat intensified aging effect. SAM maintained smoothness and balanced tone across both stages but introduced slight softening around the eyes and mouth that reduced perceived realism compared to FADING.

In the case of the **Black Female**, FADING effectively retained core identity features while applying gradual aging transformations. Nonetheless, at ages 60 and 70, a perceptible darkening of the skin tone and deepening of wrinkles were observed. SAM produced more uniform tones and softer transitions but at the cost of reduced facial definition, particularly in the 70-year image.

For the **Asian Female**, both models generated coherent and visually plausible aging results. FADING applied moderate textural aging, maintaining identity and cultural features, whereas SAM exhibited subtle smoothing and minor loss of depth perception in older outputs. The overall appearance remained realistic, with minimal artifacts in both models.

Finally, in the **Indian Female** example, FADING consistently preserved identity and cultural markers such as jewelry and clothing details. The aging progression appeared natural up to 70 years, although minor facial rigidity was observed. SAM achieved smoother but less defined transformations, with occasional fading of cultural details. FADING thus provided slightly more faithful and visually realistic representations in this demographic group.

In summary, across all demographic groups, both models produced generally realistic aging transformations. However, the most pronounced visual distortions occurred at the 60- and 70-year stages, consistent with the quantitative results reported in the previous section. FADING tended to generate more detailed and biologically plausible outcomes, while SAM favored smoother, more cosmetically refined appearances, occasionally at the expense of fine facial detail.

4 Conclusion

This study presented a comprehensive evaluation of two facial aging models: **FADING (based on Stable Diffusion)** and **SAM (based on StyleGAN)**, focusing on **identity preservation** and **visual realism**. Using a demographically balanced dataset, we assessed performance across ethnicities, genders, and aging stages (30 to 70 years), providing a systematic and equitable comparison framework.

Quantitative and visual analyses consistently showed that **FADING generally outperforms SAM** in preserving identity across most age groups and demographic categories. In particular, **FADING demonstrates a pronounced advantage for Black and Indian females**, while differences are smaller but still present for Asian and Indian males. Although SAM produces aesthetically smoother outputs, its tendency to alter facial structure in older age predictions reveals limitations in **identity retention and fairness**. SAM exhibits greater performance variability, especially in older age groups (60–70 years), with higher rates of misclassification and identity drift. In contrast, **FADING shows improved demographic balance**, with fewer and less severe disparities across ethnic and gender groups. On the image level, **FADING produces realistic and identity-consistent results**, though it occasionally exaggerates aging traits (e.g., deep wrinkles or skin tone changes in older ages), whereas SAM, while visually cleaner, often fails to maintain identity in multiple non-White cases.

In summary, this work highlights the importance of **combining quantitative evaluation with perceptual analysis** to assess facial aging models holistically. As a limitation, this study employed only the **ArcFace model** for identity verification and did not include a **human-based perceptual evaluation**, which limits generalization but ensures methodological transparency. **Future research should focus on bias mitigation strategies** and explore **hybrid diffusion-GAN architectures** that leverage the strengths of both approaches. Expanding and diversifying the training dataset will also be essential to advance **fair and effective synthetic aging systems**.

Overall, these findings reinforce the need for fairness-oriented evaluation in facial aging research and highlight diffusion-based architectures as promising tools for identity-consistent and demographically balanced age synthesis.

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References

[1] Fórum Brasileiro de Segurança Pública. Anuário Brasileiro de Segurança Pública 2024. https://forumseguranca.org.br/, 2024.

[2] I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio. Generative adversarial nets. In Z. Ghahramani, M. Welling, C. Cortes, N. Lawrence, and K. Weinberger, eds, *Advances in Neural Information Processing Systems*, volume 27. Curran Associates, Inc., 2014.

[3] A. Ramesh, P. Dhariwal, A. Nichol, C. Chu, and M. Chen. Hierarchical text-conditional image generation with clip latents, 2022.

[4] J. Ho, A. Jain, and P. Abbeel. Denoising diffusion probabilistic models. In *Proceedings of the 34th International Conference on Neural Information Processing Systems*, NIPS '20, Red Hook, NY, USA. Curran Associates Inc., 2020.

[5] M. Mirza and S. Osindero. Conditional generative adversarial nets. *arXiv preprint arXiv:1411.1784*, 2014.

[6] T. Karras, S. Laine, and T. Aila. A style-based generator architecture for generative adversarial networks, 2019.

[7] X. Chen and S. Lathuilière. Face aging via diffusion-based editing. In *34th British Machine Vision Conference 2023, BMVC 2023, Aberdeen, UK, November 20-24, 2023*. BMVA, 2023.

[8] Y. Alaluf, O. Patashnik, and D. Cohen-Or. Only a matter of style: Age transformation using a style-based regression model. *ACM Trans. Graph.*, vol. 40, n. 4, 2021.

[9] Y. Zhang and W. Deng. Class-balanced training for deep face recognition. In *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, pp. 3594–3603, 2020.

[10] G. Huang, M. Mattar, T. Berg, and E. Learned-Miller. Labeled faces in the wild: A database forstudying face recognition in unconstrained environments. *Tech. rep.*, 2008.

[11] J. Deng, J. Guo, N. Xue, and S. Zafeiriou. Arcface: Additive angular margin loss for deep face recognition. In *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 4685–4694, 2019.

[12] S. I. Serengil and A. Özpinar. A benchmark of facial recognition pipelines and co-usability performances of modules. *Bilişim Teknolojileri Dergisi*, 2024.

[13] S. I. Serengil and A. Ozpinar. Lightface: A hybrid deep face recognition framework. In *2020 Innovations in Intelligent Systems and Applications Conference (ASYU)*, pp. 1–5, 2020.