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Facial Aging Prediction Challenges and Developments: A Review

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***Abstract* - Our world today is full of development and people have become obsessed with beauty and maintaining the continuity of youth and fear of facial aging, which represents gradual changes in physiological functions. Hence, the need to simulate facial aging has emerged. Recently, many contributions have spread that have addressed this phenomenon. In this paper, we highlight many facial aging methodologies: the traditional approach, the deep learning approach, and the hybrid model approach. Regarding the feature-based approach, we will explain its strengths and weaknesses. Then we will highlight the methodologies based on deep learning, especially the competitive generative networks that have improved the accuracy and realism of facial aging images. We will also explain the strengths, weaknesses, and possible improvement. In addition, we will mention the hybrid models and their strengths and weaknesses. The datasets used in this work are presented. Furthermore, we will explain how to deal with the challenges associated with facial aging estimation, starting with the obstacles that accompany the dataset, warnings about privacy and ethical considerations, with the need to address these challenges to ensure the safe and ethical use of the techniques, and discuss the impact of the unbalanced distribution of the dataset, and touch on some of the criteria for evaluating these methods. Finally, we present a future vision on the emerging trends, challenges and future directions in the field of facial aging in order to help guide future research in the right direction.**

Keywords: Age Progression, Conditional Attention Normalization (CAN), Facial aging estimation Generative Adversarial Networks (GANS, Enhanced Super-resolution Generative Adversarial Network (ESRGAN).

I. INTRODUCTION

Predicting facial aging is the process of simulating the effects of aging on the face during image generation, reflecting the changes that accompany the aging process. This research area has gained significant importance in computer vision and pattern recognition. This technology possesses enormous potential and has several uses in various fields, such as forensic medicine. The process of predicting a person's appearance in various age stages is of great importance and is invaluable. This technology offers a number of important practical applications in various fields due to its ability to represent the changes that occur in a person's face with age. Its real- world applications are represented in the field of law enforcement by helping to find missing or suspected individuals by generating facial aging images through which government agencies can provide representations of a person's appearance in different age stages, which increases the chance of finding them, who may have potentially changed their appearance. The process of predicting facial aging enables [1].

Facial aging prediction is very helpful in reconstructing the features of victims or suspects based on the information provided, such as old photos or information provided by eyewitnesses about the features of the suspects, which enables investigators to find research clues and narrow the scope of the search for suspects, which helps in providing useful analyzes in criminal cases. Human trafficking is a serious threat that threatens the countries of the world today. According to the latest report in 2020 on human trafficking issued by the United Nations Office on Drugs and Crime, the number of victims of human trafficking worldwide has reached about 34%, and they are children [2].

This technology also has applications in many vital areas such as biometrics and human- computer interaction [3] in the field of biometrics, accurate prediction of a person's appearance at different ages enhances the effectiveness of facial recognition systems for identification and verification purposes by taking into account the changes in facial features that accompany the aging process. It is obvious that all human faces follow the same behavior in terms of fat loss to the appearance of wrinkles during aging, and that these changes are measurable depending on race and specific lifestyle behavior [4] [5].

Facial aging estimation technology is of great importance in the context of health care and aging research. Through accurate prediction of facial aging pathways, this technology has helped [6]. In addition, facial aging estimation technology is of great importance in the context of health care and aging

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research. Through accurate prediction of facial aging pathways, this technology has helped doctors and researchers to gain insights into the effects of aging on an individual's health and well-being. This includes diagnosing age-related changes in facial morphology associated with certain medical conditions, monitoring disease progression, and developing personalized interventions to address age-related health issues. Facial aging estimation technology also contributes to raising awareness of the importance of healthy aging and preventive care by linking lifestyle choices with potential effects, such as sun exposure, smoking, and skincare routine, on facial aging.

Mimicking complicated transitions [7] Changes in facial features, shapes, and textures that occur as individuals age help in predicting facial aging. Both genetic, environmental, and lifestyle choices play a fundamental role in creating these changes, which negatively affects finding the subtle differences of aging accurately.

Researchers have discovered various methods to address facial aging, each with its own strengths and limitations. The quality and diversity of the database is the basis of success [8]. These methods are largely. Although many datasets are used in facial aging research, they often suffer from limitations related to biases in age, race, and demographic representation, which poses a significant obstacle for researchers in collecting and organizing data.

It is worth noting that the process of simulating facial aging while preserving the individual's identity faces several challenges [9] because this simulation process leads to clear changes in facial expressions, the lack of sequential data in the dataset because most datasets such as CELEBA and FFHQ do not contain sequential images of the same individuals at different age stages. There's also several factors that affect facial aging, such as gender, race, genetic factors, and the lifestyle used, Another challenge is the difficulty of balancing the fine details and speed of generation of aging models, in addition to the lack of evaluation criteria that accurately measure the quality and realism of the generated images while preserving the individual's identity. The rest of the research paper is organized as follows:

This paper is divided into six sections. Section 1 provides an introduction to the topic of facial aging The second section provides an in-depth examination literature on facial aging, with a focus on the different methods that have been used to study this phenomenon makes a comparison between these methodologies .a discussion of the challenges and opportunities in this field. Section 3 provides a critical evaluation of the current datasets used for training and validation, highlighting their strengths, limitations, and directions. It also considers the ethical considerations associated with facial aging datasets, emphasizing the importance of publishing in an honest manner, avoiding the dissemination of inaccurate information, and minimizing the risks associated with privacy and bias. Section 4 explores Challenges in Facial Aging Prediction. Section five focuses on the different evaluation methods available for assessing the accuracy of the algorithms discussed in the paper. Finally, Section six concludes the paper by summarizing the findings and outlining the challenges and future directions in the field of facial aging.

II. LITERATURE REVIEW

In the field of facial aging prediction, models have been reviewed by many studies, which included: Traditional Feature-Based Approaches generative adversarial networks (GANs), and hybrid approaches.

Feature-based approach relies on both the extraction and analysis of facial features (wrinkles and lines) manually, which are used to predict the effects of aging based on statistical models and expert analysis. Although this approach provides clear explanations of the processes that occur during aging.

There are some limitations that it suffers from due to its heavy reliance on analysts' expertise and its inability to generalize the results to different datasets. In contrast, the deep learning approach takes advantage of the power of neural networks, especially generative adversarial networks (GANs), to generate realistic images that simulate the aging face by learning from large datasets.

Figure 1 [10] illustrates examples of aging facial images generated by CGAN. Hybrid models combine the traditional approach with the deep learning approach, contributing to more accurate and effective solutions. They extract and analyze features manually and employ deep learning techniques to solve the generalization problem by learning from large data sets. Hybrid models can use deep learning techniques to build systems capable of generating realistic images that simulate aging.

This is done by relying only on available data, which helps reduce the bias resulting from relying on human experience, as these models enhance the improvement of the processes that occur during aging.

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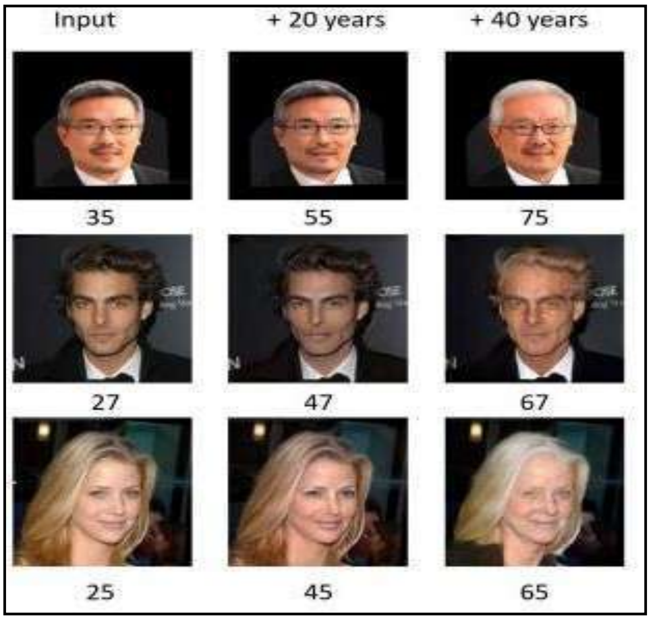

Figure 1: Face Age Progression [10]

2.1 Traditional Feature-Based Approaches

Feature-based methods are based on robust techniques that are fundamental to understanding how an individual's face varies with the progress of time. These techniques often involve manual or semi-automated analysis of custom facial features, such as wrinkles, skin texture and facial features, differences in skin color and how fat is distributed over facial areas you.

These methods are based on extracting basic features and characteristics from facial images [11] Using image processing techniques such as Jabber filters, Fourier transforms, land mark, and after the extraction process, statistical models such as linear regression or key component analysis (PCA) are used to understand the relationship between these traits and age markers. In addition, techniques such as HOG (Histogram of Oriented Gradients) or LBP (Local Binary Patterns) can also be used to ensure efficient skin texture and wrinkle analysis.

Template-based methods are based on categorized facial images [12]. This is done by comparing the main features of the face between templates and target images so that the images are modified to be compatible with the facial features at the specified age, these methods modify the structure of the face, creating copies that simulate the changes that occur during aging. While the feature-based approach focuses on extracting and analyzing individual features, it means that the template-based approach is less flexible in dealing with features. There are a large number of practical applications of these technologies, such as facial recognition systems, age estimation in security, and there are also a number of challenges such as differences in gender, race, standard of living and lifestyle (such as smoking, sun exposure), which have a shameful impact on the accuracy of age estimation.

Kemelmacher-Shlizerman *et al.*, 2014 [13] introduce fully computerized approach to facial aging, focusing on the challenge of age progression in children. It presents a comprehensive method for the natural progression of facial images across different age. This dataset is used to generate images where facial features for each age group remain smoothly adjustable, while key facial landmarks retain their positions. Lighting effects can also be added to enhance the accuracy of predictions and achieve more realistic images. Singular Value Decomposition (SVD) is applied to the aligned images to analyze facial features and simplify the data. Optical flow technology is employed to analyze a sequence of consecutive images of a scene and identify changes in pixels, which helps in calculating age-related transformations. Since the effectiveness of the algorithm relies on the quality and diversity of the training dataset, the lack of sufficient representation for all age groups, ethnicities, and facial characteristics may lead the algorithm to face challenges in accurately aging faces for diverse populations.

Shu *et al.*, 2015 [14] introduce one of the earliest to address facial aging analysis, consists of two phases: an offline training phase and an online image generation phase. In the first phase, aging dictionaries that cover diverse aging characteristics are created by collecting pairs of aging. A developed machine learning model based on a dictionary was used, taking into account individual details such as birthmarks and scars. Principal Component Analysis (PCA) was used to reduce dimensionality. To achieve consistency with the training phase and obtain natural-looking faces, data-driven learning techniques and iterative optimization techniques were used. A visual comparison was conducted by 50 people, where 45.35% preferred this model, 36.45% preferred previous work, and 18.20% considered them equal.

Yamamoto *et al.*, 2017 [15] presents a study aimed modifying facial age in videos while considering the dynamic changes that occur over time in facial expressions by generate videos that simulate facial aging while taking into account the wrinkles produced in facial expressions. Facial expressions in the video are matched with the data set of videos displaying similar expressions. To facilitate the matching process, Local Binary Patterns (LBP) are used to describe the subtle changes in facial expressions. To ensure that the changes in the face (expressions or wrinkles) evolve coherently and consistently over time in the video, Dynamic Time Warping (DTW) is applied using Radial Basis Functions (RBF). This technique is used to precisely adjust the shape of the frames in the video to match the corresponding shape in the target video to ensure

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that each facial expression in the database matches the target frame correctly.

Tang *et al.*, 2017 [16] builds upon previous research by addressing the field obstacle of finding long-term aging sequences. This is achieved by maximizing the use of dense short- term aging pairs, which supports the possibility of real-world application. It encourages the use of a dual-level dictionary, This ultimately leads to more realistic images that simulate aging. To reduce computational complexity, improvements were made in the age generation process, resulting in the model's speed in reaching the desired results with a smaller number of training cycles during the face generation process. A visual comparison was conducted by 50 people, where 36.5% of them preferred the proposed model, while 26.7% preferred previous work.

Elmahmudi, A., & Ugail, H. 2021 [17] presented work which relied on ethnic facial templates generated based on gender, color, texture, and age characteristics. The system consists of two main components: the first is a mathematical approach to generating ethnic-specific aging templates using a mathematical method to construct aging templates for each ethnicity based on average faces that represent a collection of important facial features for each ethnic group, which are adopted as a model that reflects the common characteristics while in the second, these templates are applied to the target faces to generate age .with the inclusion of parameters that control color and texture properties. Convolutional Neural Networks (CNNs) were used to verify the accuracy of the generated faces. The data collection process includes several stages. To achieve accurate age progression or reversal, transformation and modification techniques were used through image distortion techniques, which change the shape of the face in a way that simulates the aging or reversal process, and parameters were also integrated to control the accuracy of facial features in proportion to age and color to ensure the realism of the images.

Sinha & Barde, 2022b [18] proposed system that consists of several stages. The processing stage begins by identifying landmarks, and then applying geometric transformation to adjust the position of the face and applying warping to modify the image to match the desired face model. Finally, normalization is applied. A PCA model was used to extract and reduce the dimensions of the features. An SVM model was used to classify the face image according to age group. The use of PCA helped to improve the accuracy of facial recognition. Also, the multiple stages of the methodology enhanced the effectiveness of the system, In addition, When applied to the FEI data set, it achieved a similarity score exceeding 70%.

Sinha & Barde, 2022 [19] introduce a system for time-invariant face recognition, which consists of four stages: face detection, image pre-processing, feature extraction, and feature classification. In the first step, the face in the image is detected. In pre-processing, the face is aligned and then cropped and noise is removed. To extract facial features in the image, Principal Component Analysis (PCA) is used. In the classification process, a multi- class support vector machine was used. The proposed system enjoyed efficient results in the face recognition process and the identification of the individual and the elimination of the challenges that arise with age.

Although traditional methods have provided valuable insights into the natural transformations of facial aging, they cannot capture the complexities that would better explain the aging process. Therefore, advanced techniques have emerged, particularly those based on machine learning and deep learning, to overcome obstacles and improve the quality and accuracy of facial aging models to provide more realistic images.

Table (1) shows a brief summary of the algorithms used in facial aging research in the feature-based approach, in addition to the data sets used to train and evaluate these algorithms. Each algorithm is explained precisely in terms of publication history, data set used, strengths, weaknesses, and possible improvements.

Table 1: Summary of the algorithms used in facial aging research in the feature-based approach

Paper title	Data set	Strong point	Weak point	Proposed Improvements
Kemelmacher-Shlizerman *et al.*, 2014 [13]		A huge database of the Internet has been compiled, the ability to produce multiple aging images from a single image.	The system was based on only face images without the head and upper torso, the model depended on the quality of the inserted images, the loss of fine details when aging.	Developing modern techniques to improve the quality of input images, expanding the database to include the head and torso and using techniques to improve fine details during facial aging.
Shu *et al.*, 2015[14]	CACD, MORPH,	Relying on personality traits during aging and training.	Dependency on data quality, the model was complex, the	Improving the process of long-term data collection, using advanced

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	FGNET	The dictionaries were created using databases of similar age groups. The process was divided into two layers: an aging layer and a personal traits layer. Please provide an English translation.	method was based only on pairs of faces of similar age.	techniques to analyze the individual characteristics of people to raise the accuracy of the model to reduce computational costs, requires improving education algorithms, using modern technologies, and focusing on the reverse process of aging.
Yamamoto *et al.*, 2017[15]		The model's reliance on videos instead of still images, which distinguishes it over previous methods, the method generates facial changes tailored to the target age.	The model is complex and requires high computational resources, the model's dependence on video quality, as well as the limitations of the database.	Develop techniques that automatically improve video quality, improve the accuracy and speed of the model using machine learning techniques.
Tang *et al.*, 2017 [16]	CACD, MORPH	The age prediction technique depends on the personal characteristics of each individual, each dictionary dedicated to training on the characteristics of aging for a specific category.	Problems in the data collection process, model complexity, model dependence on short-term pairs of faces.	Expanding the process of collecting short-term pairs of faces, improving the method of building dictionaries to improve the accuracy of the model and using modern techniques to ensure the generation of more realistic faces.
Elmahmudi, A., & Ugail, H. 2021 [17]	FEI, Morph II	little use of computational resources, relying on a known database, which helps to easily compare it with other research, in addition to using several measures to verify the accuracy of the system such as cosine similarity and structural similarity.	Generalization problems, the templates used are due to certain and specific categories, which limits the ability of the model, in addition to the fact that the model does not take into account the dynamic changes of faces over time.	Use advanced techniques to achieve more accurate results, the ability to integrate dynamic changes, in addition to using various data, Expand the scope of research to include practical applications such as security, entertainment and the medical field.
Sinha & Barde, 2022b [18]	FEI, MORPH II	Multiple stages helped the system in face detection and image processing, the system has the ability to adapt to age changes.	There are still challenges in facial detection due to minor changes, the dependence of the results on the quality of the inserted images, the high sensitivity of facial posture changes.	It is possible to improve the performance of the system by using advanced techniques in both the feature extraction and classification process, developing techniques that are more tolerant of postural changes. It is also possible to improve the accuracy of the system by integrating it with deep learning techniques such as CNN.
Sinha & Barde, 2022 [19]	FEI	The model's ability to recognize faces taking into account age changes, speed in performance, use of advanced techniques.	The model's reliance on the database, limiting its ability to generalize to other databases, deep learning techniques that may increase the accuracy of the model.	Overcoming generalization problems by training the model on larger databases, in addition to the possibility of using convolutional neural networks and using deep learning techniques in the classification process to improve the accuracy of the model.

2.2 Generative Adversarial Networks

Unlike feature-based methods, generative adversarial networks (GANs) have emerged as a powerful option [20] in the field of facial aging. The underlying principle of GANs is adversarial learning, where two neural networks compete: a generator network that creates realistic images of faces at different ages, and a discriminator network that aims to distinguish between the original images in the dataset and the generated images. The following equation illustrates the principle of the work of generative competitive networks.

$$\min G \max D\,(D,G) = E\,x{\sim}Pdata(x)\,[\log D(x)] + E\,(1)\,z{\sim}Pz(z)\,[\log(1 - D(G(z)))]$$

The generator, denoted as G, takes as input a noise vector (z) composed of random numbers. It transforms this noise into synthetic samples $(z;\,\theta g)$ where θg represents the parameters of the generator network. The objective is to map the noise

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vector into the data space, leading to the generation of synthetic data that is indistinguishable from real data.

The discriminator, denoted by D, analyzes data samples x and estimates a probability $(x;\ \theta d)$ that the sample is drawn from the true data distribution, during the training process GAN Competitive Networking. The discriminant seeks to enhance its ability to classify both real data models and the data produced by the generator expresses this goal using the term [log D(x)] in the equation, where D(x) represents the probability of the discriminant of real data models The goal of the discriminant is to approach the probability of (1) When dealing with real data, at the same time, the generator is trained to reduce the ability of the discriminant to correctly identify generated models as counterfeit. This is done by reducing the likelihood that the discriminator will give a value of 1 when providing generated data. This goal is expressed by the term $[lo(1 - D(G(z)))]$. Here, (z) represents the generated data, and $D(G(z))$ is the probability that the discriminator assigns to the generated samples. The generator seeks to make the discriminator incapable of distinguishing between real and generated data well. This dynamic competition between the two networks gradually improves their performance. This process can be likened to a 'zero- sum game' between a minimizer and a maximize, until reaching a Nash equilibrium 'where neither player can improve their situation by changing their situation'.

This indicates the difficulty of distinguishing the characteristic of the generated samples. This process continues iteratively until the ideal balance is achieved, which ultimately enables the generator to generate high-quality data. The flowing Figure 2 [21] indicated to the Generative Adversarial Networks (GANs) Architecture.

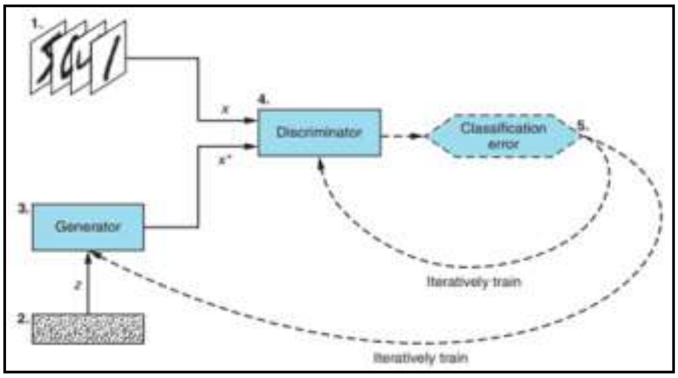

Figure 2: Generative Adversarial Networks (GANs) Architecture [21]

In contrast to traditional GANs, which often lack stability and produce noisy outputs,[22] used Conditional Adversarial Auto encoders (CAAE) have emerged with the capability of generating images that accurately reflect age-related changes. this model employs an encoder, a generator, and discriminators, The encoder compresses data, the generator produces images, and the discriminator enhances training efficiency. This approach enables smooth age transitions while preserving facial features and individual identity. the conditional generative adversarial network balances several factors, including ensuring that the generated images closely resemble the original images while preserving essential details. It is also crucial to emphasize that the generated images follow a natural distribution that mimics the real-world diversity of age-related features, resulting in highly realistic outputs. This distinguishes it from other generative models such as Variational Auto encoders (VAEs) [23] and Adversarial Auto encoders (AAEs) [24]The distinction lies in its innovative use of discriminators in both the encoder and generator, which significantly enhances the model's performance. This represents a notable advancement over traditional GANs and makes it a promising choice in the field of generative models.

Shi *et al.*, 2020 [25] introduced approach that integrates Conditional Attention Normalization (CAN) into both the generator and discriminator. CAN utilizes age differences during the normalization process, which helps to identify areas affected by the aging process, while simultaneously mitigating irrelevant information through an attention map, while preserving the individual's identity when applying aging effects. a conditional age attribute classifier was integrated with the model, which resulted in increased accuracy. To measure the accuracy of the model and ensure effective training, a target function is used that combines the adversarial loss, the reconstruction loss, and the classification loss. The GLCA- GAN model achieved a facial verification accuracy rate of 95.39%.

Sharma *et al.*, 2020 [26] presents a comprehensive approach that combines Cycle-Generative Adversarial Network and Enhanced Super-resolution Generative Adversarial Network (ESRGAN) to enhance the accuracy of generated images and improve their quality. The work aims to simulate aging to show the effects of aging. Through the integration of several models, this integration led to the generation of the best model for data generation. This study does not require pairs of images, but it has lost many details. It also requires continuous improvement, although the combination of Cycle GAN and ESRGAN has increased the complexity of the process and requires high computing resources. When applying the FACE ++SW to estimate the average age of Generated images on the IMDB-WIKI dataset, the result for the average age of the group 19 – 35 was 30.2, for the age group 35-60 was 36.5& for age group 60 and more was 61.7.

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Kim *et al.*, 2023 [25] employ three techniques. The first, a dual-state diffusion model, reconstructs images based on style and identity conditions, requiring significantly longer training times compared to traditional methods. To extract styles, a 'style extractor' is utilized, operating at a patch level. This component is computationally expensive and complex to implement. To preserve identity a (time-step-based identity loss) technique was employed, ensuring identity consistency over time. The model demonstrated a 57% improvement in face recognition accuracy compared to state-of-the-art methods and a 6.11% increase in verification accuracy. The CASIA-Web Face dataset was used as a foundation for generating synthetic faces.

Melzi *et al.*, 2023 [26] seeks to generate a dataset that appears realistic for facial recognition by combining and leveraging the power of an advanced Generative Adversarial Network (GAN) model. The GAN is trained on a large dataset of real images to learn the patterns and details needed to create new images. Diffusion models are then used to reduce noise, enhance the generated image, Synthetic datasets were generated by controlling the GAN Diff Face settings, and the generated images were compared Using two databases, VGG2 and IJB-C, the results showed the flexibility of the proposed approach. To enhance the diversity of the images generated by GANs, The proposed method suffers from the computational cost of adjusting Diffusion Models, difficulty in maintaining identity, and limited control over facial features.

Yao *et al.*, 2024 [3] aims to improve the robustness of facial recognition models, by designing a new approach that aims to evaluate the effectiveness of synthetic aging models using the CelebA-HQ dataset to generate synthetic images for different ages (20, 30, 40, 50, and 60 years) through three techniques. (SAM) is a technique for generating synthetic images that simulate the aging process while preserving the individual's identity. CUSP (Cascaded Unsupervised Synthetic Aging) is used to add gradual modification to the image structure. Age Trans GAN is a generative adversarial model specifically designed to reverse facial aging. two transfer learning models were used evaluate the generated image. The experimental analysis results revealed some limitations in preserving identity by comparing them with the results of real images, in addition to the decline in the performance of these models with large age gaps. The experimental results also showed that the recognition rate of the proposed model on synthetic aging images is 3.33% higher when tested on images with an age gap of 40 years. The approach is complex and relies on a specific type of image. Some results showed that age estimates may be inaccurate in some cases.

Krishna *et al.*, 2024 [27] developed an innovative approach to age prediction based on facial images by curating extensive and diverse datasets comprising facial images of various races and ages, image preprocessing was conducted to enhance quality, reduce noise using various techniques. Convolutional neural networks were employed for feature extraction, and generative modeling techniques to enhance image quality. To improve model robustness with new data, strategies that allow models to adapt to novel environments and incorporate attention mechanisms were implemented. Attention mechanisms were employed to identify the most salient facial features for age prediction. self-supervised learning units were utilized to learn features directly from the images without requiring a large amount of labeled data. Models were trained on GPUs. Performance metrics such as mean absolute error and accuracy were monitored during training.

Table (2) shows a brief summary of the algorithms used in facial aging research in the deep learning approach, in addition to the datasets used to train and evaluate these algorithms. Each algorithm is explained precisely in terms of publication history, dataset used, strengths, weaknesses, and possible improvements.

Table 2: A brief summary of the algorithms used in facial aging research in the deep

Paper title	Data set	Strong point	Weak point	Proposed Improvements
Z. Zhang, Y. Song, and H. Qi, [20]	MORP H, FGNET	(CAN- GAN (Conditioned-Attention Normalization GAN), which is based on Conditioned-Attention Normalization (CAN). Which works to treat facial areas differently depending on their importance, which enhances the features of aging, The accuracy of age classification was improved using Contribution-Aware Age Classifier (CAAC application flexibility.	The complexity of the model the dependency of the results on the quality of the data used in the training,	The efficiency of the model can be improved through the use of dimensional reduction techniques, as well as the integration of other deep learning techniques such as augmentative education to improve and reduce the complexity of the model, and to improve the preservation of the individual's identity, it is recommended to use metric learning techniques to ensure that the basic features of the face remain unchanged.

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Shi *et al.*, 2020 [23]	IMDB-WIKI, CACD, UTK Face, FGNET, CELEB-A	Integrating multiple technique where Cycle GAN was used to achieve aging and to improve image quality, ESRGAN was used, the work was tested on five different data sets, and Face++ tools were used to evaluate results quantitatively, which gives accuracy in measuring results such as error rate and confidence score.	The model is complicated by the use of multiple techniques such as Cycle GAN and ESRGAN and requires high computational resources, the dependence of the results on the quality of the results entered into the training process, as well as the difficulty of maintaining the identity of individuals.	Enhance the quality of the resulting images through the use techniques such as multi-stage GANs or ensemble techniques. Improving the results by increasing the diversity of data used in the training process, also reducing the computational cost through techniques that reduce the size of the model such as (Model Pruning) or quantization, it is also possible to improve the model through advanced techniques such as Reinforcement Learning to improve the accuracy of age Prediction.
Sharma *et al.*, 2020 [24]	FFHQ (Flickr-Faces-H & Real data	The experiments showed the superiority of the model and in the performance of facial recognition by 60.9% compared to previous methods, which confirms the approach of the model to the performance of the real data, the study also achieved a good balance between the diversity of the images generated and consistency in labels, which made it the best previous methods.	The model showed poor performance with the CFP-FP data set, which was characterized by the diversity of shooting modes in it, the need to maintain consistency in images due to its impact on the quality of the resulting images.	integrate three-dimensional generative models to improve the realism of images and reduce the gap between artificial data and truth, the use of advanced methods to ensure the consistency of labels in all generated images, such as the use of specialized CNN for the purpose of identity verification, in addition to increasing the diversity of data to improve the performance of the model, training the model using training data that combines real and artificial data to reduce the gap between the performance of the model on real and artificial data.
Kim *et al.*, 2023 [25]		New model (GANDiffFace) that integrates GAN and Diffusion Models that lead to the result of generating realistic images StyleGAN3 enabled demographic control of the faces generated., in addition to solving the privacy problem, as the study provided an alternative to realistic images that raise privacy concerns.	The model is complex and the process of adjusting Diffusion models requires large computational resources as well as some images contain distortions, in addition to inter-class variations.	Improving model performance by integrating other technologies such as Transformers, it is also possible to improve image quality by discovering new technologies and reducing distortions, in addition to the possibility of increasing the number of identity when improving computational efficiency.
Melzi *et al.*, 2023 [26]	CACD and Morph	A new framework that combined the conditional GAN networks and the feature routing module with the age classification unit to improve the accuracy of aging prediction with the possibility of preserving the identity of the individual, and to reduce the differences between the original image and the generated image, L2 loss was used, and to preserve the identity, Perceptual Loss was used, and it also showed high accuracy in the classification of age using L-Softmax loss. In addition to the fact that the study showed the results of high levels of confidence in maintaining identity.	The additional modules increased the complexity of the model, and the study did not take into account racial differences in facial aging, which limits the possibility of applying the model in other practical applications.	Diversity of data used in the training process to enhance the performance of the model on various scenarios, in addition to the need to make improvements in the classification unit using advanced techniques the integration of deep learning techniques to improve the performance of the model.

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Yao *et al.*, 2024 [3]	Celeb A-HQ	The method improved the accuracy of facial recognition, specifically with large age gaps, the method has flexibility thanks to the use of synthetic aging model (SAM) to generate aging images, a comprehensive analysis of the effect of age gaps on the performance of the model was also made, and realistic data such as B3FD and synthetic data such as CelebA-HQ were used.	Difficulty maintaining a person's identity compared to realistic images, the model's reliance on a specific data set, the model's performance decreases specifically with increasing age gaps.	Using more sophisticated metrics to better assess model effectiveness, eliminating generalization problems by using a more diverse dataset, and improving ageing techniques used to preserve individuals' identity.
Krishna *et al.*, 2024 [27]	MORP H, DB-Wiki.	A comprehensive analysis of age, race and gender worked on the accuracy of facial analysis, achieving high accuracy with the FGNET database where it reached 98.87%, using advanced technologies such as SAM, PCA & CNNs.	Generalization problems because the model performed poorly on the external dataset, in addition to arithmetic redundancy and consumption of time and resources due to the use of techniques such as PCA&CNNs, in addition to the model's reliance on the FGNET dataset only.	Eliminate generalization problems by expanding the dataset, integrating hybrid models such as integrating CNNs with other technologies such as Transformer to improve feature extraction, adding improvements to algorithms to be faster and more efficient in real time, respecting individuals' privacy and establishing an ethical framework to ensure that face analysis is used ethically.

2.3 Hybrid Models

They are models that combine two or more technologies for the purpose of forming a single model [28] , can work effectively and may include deep learning techniques, machine learning, in addition to improvements in the structure of neural networks. It combines the advantages of diverse models to achieve the best results, where it is possible to combine feature-based models with Generative Adversarial Network models to improve the accuracy of age prediction while maintaining the individual's identity. In the field of age prediction, hybrid models can combine [29] Between a number of advanced technologies such as deep learning techniques such as convolutional neural networks, which are characterized by their high ability to extract features with attention mechanisms techniques that help the model focus on certain information in the image, which enhances the accuracy of facial recognition at various age stages. The high potential possessed by hybrid models works to disassemble features and divide them into different components such as identity and age, which enhances the accuracy of the model and reduces interference and as a result will work to increase accuracy by taking advantage of the representative power of each technology used, hybrid models also have the ability to adapt to different types of data because they integrate various learning strategies.

Hu 2024 [30] was built regression models where age was treated as a continuous value by applying adaptive class regression and then integrating facial features to align facial. In addition to using multi-task learning to predict age along with demographic characteristics such as race and gender, and to improve generalization, the principle of joint representation learning was relied upon. The CNN was trained on different age periods and its average predictions were calculated, achieving superior results in estimating biological age, in addition to using the Age Net model to classify age into specific age groups and applying regression techniques to these groups, the research achieved advanced results in improving the accuracy of estimating biological and phenotypic work. The challenges facing the research are the non-linearity in aging and the complexity of the data, as the difference in lighting, angles and expressions had an impact on the accuracy of the models. The problem of overlapping tasks also negatively affected the performance of the model in addition to the problems of bias due to the lack of balanced data and the lack of sufficient representation in race and gender.

Shi *et al.*, 2023 [31] utilizes an advanced deep neural network model based on the multi-head self-attention mechanism, the Swin Transformer, to improve the accuracy of age prediction based on facial features the model's ability to process data in parallel makes it faster and more efficient compared to convolutional neural networks. Extract better and more accurate features. The Swin Transformer was then combined with Attention-Based Convolution (ABC). The latter works to extract information-rich areas of the face related to age.

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Wu 2024 [32] build model starting with the extraction of facial features from the face using (ResNet) to increase the accuracy of facial recognition, the use of hybrid attention mechanism (HSCAM) that combines the spatial attention mechanisms and the channel to dismantle facial features that focus on facial characteristics and the application of multiple aggregation techniques to enhance the effectiveness of the model To reduce the information exchanged between the components of identity and age, multitasking learning was applied. The study showed that the combination of spatial attention and channel mechanics in the model helped to deconstruct facial features and separate both (age features and identity features), which helped reduce the correlation between the two groups and increase the accuracy of identity recognition and age separately. The model showed superiority over previous studies and achieved accurate results in facial recognition across ages. The biggest challenge in this work was achieving a balance between prediction accuracy and maintaining identity, in addition to dealing with multiple data such as differences in race, gender, and lighting to improve the accuracy of the model.

Table (3) shows a brief summary of the algorithms used in facial aging research in hybrid models, in addition to the datasets used to train and evaluate these algorithms. Each algorithm is explained precisely in terms of publication history, dataset used strengths, weaknesses, and possible improvements.

In terms of performance analysis, both speed and accuracy, the feature-based approach is slow due to the manual feature analysis process based on analytical expertise. In contrast, the deep learning approach is faster in terms of execution due to the ability of generative neural networks to perform operations quickly and efficiently.

Table 3: summary of the algorithms used in facial aging research in the hybrid models

Paper title	Dataset	Strong point	Weak point	Proposed Improvements
Shi *et al.*, 2023 [30]	FG-NET, MORPH	The diversity of the models used and the improvement of the accuracy of the models taking into account demographic factors.	Complexity of the model, reliance on data, and inability to accurately predict sub-ages. Also non-linearity in advancing age. the problem of overlapping tasks negatively affected the performance of the model in addition to the problems of bias due to the lack of balanced data and the lack of adequate representation in race and gender.	Improving model performance by integrating machine learning models with neural models, increasing training data by collecting larger and more diverse data to reduce bias and generalization problems, in addition to finding advanced processing methods.
Hu 2024 [31]	Adience, FG-NET, MORPH Album II	The integration of technologies, which enhanced the accuracy of age prediction thanks to the self- attention mechanism, which helped to extract powerful and more accurate features and improve the performance of the model and its superiority over many modern methods.	Complexity of the model, which increases the cost of training and takes longer time, as well as the presence of overlapping features due to the increase in the number of attention heads, which reduced the effectiveness of the model.	Improve model performance by developing other algorithms such as Vision Transformers (ViTs), Or an improvement in Swin Transformer, Solve generalization problems, expands the database, and includes images from different environments and different lighting conditions. Reduce the complexity of the model by using techniques that reduce the number of parameters without affecting the accuracy of the model such as pruning or quantization techniques.
Wu 2024 [32]	CACD-VS, Age DB-30, and FGNET	Accuracy of facial recognition has been improved at different age stages, in addition to the possibility of separating age features well, and thanks to various aggregation techniques, information for basic features has been preserved.	Computational complexity as a result of the use of attention mechanisms and various collection techniques, as well as the accuracy of the model was dependent on the quality of the data in addition to problems in generalization.	Considering the expansion of the database to include other types of imaging and lighting environments, making improvements to the Hybrid Spatial-Channel Attention Module HSCAM mechanism for the purpose of improving the allocation of parameters, applying different types of attention mechanisms and choosing the best one, making more use of multi-tasking learning technology for the purpose of improving performance by using models that combine age and identification of people.

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Regarding data requirements, the feature-based approach requires somewhat limited datasets and relies on specialized analysis, statistical expertise, and human expertise. It is a process that requires careful analysis of facial features and focusing on the most important features such as wrinkles, fine lines, and pigmentation. Therefore, it is less efficient when dealing with complex images, as it faces several challenges when dealing with subtle differences in facial features.

As for the deep learning approach, in which the analysis and feature extraction process is done automatically and at high speed by convolutional neural networks (CNNs), it also requires large and diverse datasets to train the models efficiently, which helps to learn the patterns and minute details in the images. Therefore, it is more efficient when dealing with complex images as it can capture the fine and subtle details in facial features.

Hybrid models, on the other hand, strike a balance between speed and accuracy as they combine automatic feature extraction and human expertise. They are faster than the automatic approach because the extraction process is done automatically through deep learning, and they do not require a large dataset as is the case with pure deep learning models. Therefore, they are more resource-efficient. In terms of data needs, the feature-based approach can work with a small dataset, but in return requires high experience in the feature extraction process because it relies on human experience in extra/cting important features. While in deep learning-based models, they need big data in order for the model to train effectively and be able to learn the exact patterns of facial features. Hybrid models are more balanced in terms of their data needs as they can work with less data and at the same time can take advantage of manually defined features and in terms of adaptation, they are more flexible and adapt to different data sets.

Considering resource consumption, the curriculum varies from one type to another, where in the feature-based approach, the models are not complex and therefore less resource-consuming, and as a result, these models are suitable for resource-limited devices such as mobile devices. In contrast, the deep learning approach for the purpose of training models needs huge computational resources and is based on powerful devices such as GPUs and TPUs, in terms of resource efficiency, hybrid models come to the fore, as they combine the combination of limited features manually and automatic learning, which is suitable for practical applications due to limited resources and the urgent need for high accuracy.

III. FACIAL AGING DATASETS

Acquiring a comprehensive facial aging dataset presents a significant challenge. The collection process necessitates meticulous research and adherence to specific criteria. Ideally, each individual within the dataset should be represented by images captured at various age stages. This ensures the dataset encompasses a diverse range of aging patterns, facilitating the development of highly efficient facial aging models. While sequential images of the same individual at different ages are preferable, they are not strictly mandatory. Numerous studies on facial aging have successfully generated aging images without relying on such sequential data. Consequently, a careful evaluation of the dataset is essential to construct a robust model. The superiority of Generative Adversarial Networks (GANs) in efficiently generating realistic images that reflect facial aging necessitates the existence of diverse and efficient datasets. This is crucial for effectively analyzing the complex and nuanced patterns of facial aging. Research on facial aging has relied on datasets that vary in size, subject matter, classification metrics, and image distribution.

Ethical considerations related to facial aging datasets are paramount, especially those containing images of children. While such datasets provide invaluable insights, they raise significant concerns regarding privacy and obtaining necessary permissions. Mitigating these concerns is essential to ensure the conduct of reliable research, leading to the exploration of alternative research methodologies such as generating synthetic images. One of the recent researches addressed [33] this issue and worked hard to address it, as it presented an innovative approach to generating synthetic images of children that closely match real faces, thus eliminating the need to use real images. A specialized model for generating high-quality synthetic images of children's faces. In the first stage, images of children were collected to form a training dataset, and then StyleGAN2 was used as a basis for generating images and training a Child GAN model separately for boys and girls, where the model was improved to achieve high quality and realism in the generated images. The Child GAN model was developed to generate facial data for children separately for boys and girls, and to modify facial features, noise addition techniques were used in the latent space to enable the model to generate images with different lighting conditions, various expressions, and different ages. The generated data is classified into two distinct classes. The model uses transfer learning techniques to reduce training time and improve performance. This work combined advanced deep learning techniques with data to generate realistic and high-quality children's images.

Morph-ALBUM1 [34] This dataset is one of the earliest to be adopted in research, comprising 1990 gray scale images captured from 515 individuals. Each 8-bit gray scale image is accompanied by descriptive metadata such as age, gender, race, and date of capture. The dataset exhibits an imbalanced age distribution, with a predominance of individuals aged

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between 18 and 29. Morph-ALBUM2 [35] Comprising 5500 facial images from 3000 individuals, this dataset has been extensively used in machine learning and computer vision research for evaluating and developing algorithms for age prediction and facial recognition. The dataset spans ages from 16 to 66 years and includes metadata such as subject ID, race, gender, image capture date, and date of birth. Compared to the first model, the age distribution in this dataset is more balanced, leading to improved model performance in learning aging patterns for each class. FG-Net [24] The dataset comprises 1002 facial images from 82 individuals. It includes metadata such as age and ID number. However, the dataset suffers from an imbalanced age distribution and a limited sample size, with a preponderance of younger individuals. Consequently, it is challenging to develop models that can represent facial aging effectively. This dataset has been used to study how facial features change with age, to develop facial recognition models, and to improve age estimation. Adience [35][36] Comprising 26,580 facial images from 2,984 individuals, the dataset is divided into eight age groups: 0-2, 4-6, 8-12, 15-20, 25-32, 38-43, 48-53, and 60+. The dataset includes metadata on gender and identity. The age distribution is skewed towards younger individuals.

CACD [36] [37] the dataset comprises 163,446 images of approximately 2,000 celebrities spanning the years 2004 to 2013. Additional metadata includes year of birth, celebrity ranking by name, and identifier. The dataset features celebrities across various age ranges, though the predominant age group is 20-60 years, despite a relatively balanced overall age distribution.

IMDB-WIKI [38] the dataset comprises 523,051 facial images from 20,248 individuals, sourced from IMDB and Wikipedia. It includes metadata such as date of birth, time of image capture, gender, celebrity name, celebrity ID, age, and facial location. The age distribution is skewed, with a preponderance of individuals in the 20-30 and 30-40 age groups. Furthermore, the age distribution is imbalanced across both younger and older age groups. Age DB [39] The dataset comprises 16,488 images of 568 individuals, with ages manually annotated on each image to ensure accurate labeling. The average number of images per individual is 29. The gray scale images include metadata such as individual name, age, and identifier. While the dataset exhibits more balanced age distribution compared to others, the majority of individuals fall within the 30- 40 age range. Notably, the dataset spans a wide age range from 0 to 112 years, encompassing various facial expressions (e.g., smiles, neutral expressions) and poses. Due to its diversity, the dataset is well-suited for evaluating age prediction models under various conditions. The images were collected from diverse environments, and ages were meticulously annotated manually along with subject name and identifier.

UTK Face [40] the dataset comprises over 20,000 facial images, providing information on age, gender (male or female), and race (Caucasian, Asian, African, etc.). The images encompass a wide range of age groups, from infants to the elderly. This dataset is utilized for face generation and to enhance the accuracy of classification based on age, gender, and race. While the age distribution exhibits a degree of balance, there is a predominance of individuals within the 10-19 age group.

It is noteworthy that an imbalanced distribution [39] of a dataset will lead to inequitable training, where the model may receive unequal amounts of information from different age groups. Consequently, the model will become proficient at predicting the most common age groups in the data, while struggling to accurately predict less frequent age groups. Additionally, this imbalance can introduce biases into the model, causing issues in real-world applications due to the discrepancy between the actual age distribution and the training data distribution. Similarly, an imbalanced distribution of races leads to underrepresentation, resulting in inadequate training and negatively impacting the prediction accuracy of the model. Moreover, it will cause generalization problems [41] when applying the model to new datasets with diverse races. To mitigate these issues, it is recommended [42]to collect a balanced dataset in terms of age and race distribution. Furthermore, data augmentation techniques can be employed to increase the number of samples in underrepresented groups. Additionally, resampling techniques can be applied to ensure an equal distribution during training. Finally, algorithms that specifically address imbalanced data should be utilized. Sample images from each group are illustrated in the figure 2[43].

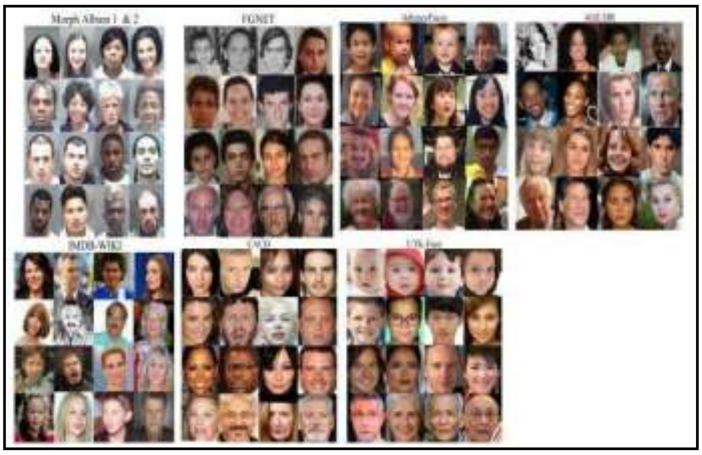

Figure 2: Dataset sample image [43]

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IV. CHALLENGES IN FACIAL AGING PREDICTION

The most important challenge is how to balance both visual accuracy and the accuracy of the aging process, with the need to preserve the identity of the person in the images generated, despite the progress that has been made in improving each aspect individually, but achieving perfect results in all these dimensions at the same time is still a task that needs more efforts. Ethical considerations pose significant challenges in the development and deployment of facial aging technology. Primary concerns include privacy issues, obtaining informed consent, and the potential for misuse of generated images. A pressing need exists for the establishment of robust ethical frameworks and guidelines. Future research must delve deeper into the ethical implications and develop mechanisms to ensure secure usage. Scalability and computational efficiency remain ongoing challenges, especially with the growing demand for real-time and large-scale aging applications. Developing faster and more computationally efficient algorithms is crucial for practical applications in fields such as law enforcement, entertainment, and healthcare.

Ethical considerations are a major challenge in the development and deployment of facial aging technology. The main concerns are privacy issues, obtaining consent, and the possibility of misuse of the generated images. Therefore, there is an urgent need to develop strict ethical frameworks and guidelines, which requires future research to explore the ethical implications more deeply, and work to produce mechanisms that ensure safe use with the need to comply with privacy laws and regulations such as (federal education) to analyze data without transferring it outside the device and develop mechanisms that work within the framework of Ethical work to ensure the protection of personal data used in the training process, which will lead to increased confidence in the use of these technologies. The issues of scalability, computational efficiency, and the sustainability and efficiency of models remain ongoing challenges, especially with the increasing demand for real-time and large-scale age progression applications, and the scarcity of research that has addressed this problem. Therefore, the development of faster and more efficient algorithms in terms of computational resource consumption and lightweight models that can be run on smartphones, and the use of techniques such as model reduction and quantization to enhance efficiency will generate applicable models in real-world environments while reducing resources.

V. EVALUATION METRICS AND TECHNIQUES

Smart models seek to simulate the effects of facial aging with quality and realism, and they strive to predict these changes before they occur. To ensure the efficiency and effectiveness of these models, the performance of facial aging prediction models must be evaluated based on a variety of criteria to assess the quality of the results. These criteria vary and depend on the structure of the model used. Some focus on the accuracy of the prediction model, such as the Mean Absolute Error (MAE). Others focus on assessing the visual similarity between the generated images and the real world, in terms of detail and structure, such as the Structural Similarity Index (SSIM). Some focus on assessing the quality and realism of the generated images, such as the Frechet Inception Distance (FID). Others focus on assessing the extent to which the model preserves an individual's identity under various conditions. The choice of any of these criteria depends on the nature of the data and the objectives of the study, which provides a comprehensive analysis of the system's performance and enhances its quality in predicting aging patterns. A brief explanation of Common evaluation criteria is given below:

5.1 Mean Absolute Error (MAE)

It is a statistical criterion used to calculate the absolute [44] difference between the expected values and the actual values in any predictive model and can be expressed by the following equation:

$$\mathbf{MAE}=n1i=1\sum n|\,yi-y^\wedge i|$$

Where n represents the number of samples, yi is the predicted value, and y^i represents the actual value. It is used to evaluate the accuracy of facial aging prediction models by calculating how close the predictions are to the actual data. MAE helps in selecting the most accurate model based on the average error in predicting aging features such as wrinkles or skin color changes. It also helps in detecting problems in the dataset and is characterized by its robustness against outliers, ease of interpretation, and its suitability for non-linear data.

5.2 Structural Similarity Index (SSIM)

It is a statistical criterion used to evaluate the[45] visual similarity between two images based on structural properties (such as lighting, contrast, and structural details). It can be expressed by the following equation:

$$\mathbf{SSIM}(x,\mathbf{Y})=\frac{(2\mu x,\mu y+C1)(2\sigma xy+C2)}{(\mu x^2+\mu y^2+C1)(\sigma x2+C2)}$$

Where μx, μy represent the average luminance of the two images x, y, σx2 and σy2 represent the variance of the two images, σxy represents their common variance, and c1 and c2 represent constants to achieve numerical stability. The value of SSIM ranges between (1 and -1), where (1) indicates a perfect match between the two images. It is used to evaluate the visual

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quality of aging images, comparing predicted images with actual aging images to ensure structural details are preserved. It is also used to improve the training of AI models by improving training by reducing structural differences between the generated images and the baseline images, and to ensure that the predicted wrinkles appear natural in terms of location and shape. Visual similarity, which is closer to human assessment, reflects a high sensitivity to structural details, detecting differences in basic facial features such as sagging.

5.3 Frechet Inception Distance (FID)

It is a statistical criterion used to evaluate [9] the quality and realism of images generated by artificial intelligence models by measuring the distance between the statistical distribution of the real and generated image features. It relies on the pre-trained Inception-v3 network to extract features and is expressed by the following equation:

$$FID=\|\mu_1-\mu_2\|^2+Tr(\Sigma_1+\Sigma_2-2\Sigma_1\Sigma_2)$$

μ_1 and μ_2 represent the average features of the real and generated images. Σ_1 and Σ_2 represent the covariance matrices. The lower this metric, the greater the similarity between the generated and real images in terms of quality and statistical distribution. It is used to evaluate the realism of facial aging images by comparing the statistical distribution of features in the generated aging images with the distribution of real images. It helps determine the realism of generated images, such as wrinkles. It is an essential tool for training StyleGAN or CycleGAN models, where the model is optimized to reduce the FID value, which helps reduce the difference in visual features between the real and generated images. The closer this value is to zero, the higher the quality of the generated images. It measures the similarity at the level of features extracted by Inception-v3, which helps improve image quality. It is characterized by its ability to detect general pattern mismatches between real and generated images, in addition to its suitability for complex data.

5.4 Identity Consistency Metrics

It is a metric used to evaluate the extent to which an individual's identity [31] is preserved in the generated images compared to the original image. It is often based on pre-trained facial recognition networks to extract unique identity features (such as the eye contours of the generated and original images, the nose, and facial features). It is expressed by the following equation:

$$\text{Identity Score} = \frac{\| \text{Embedding}_{\text{original}} \| \cdot \| \text{Embedding}_{\text{generated}} \|}{\text{Embedding}_{\text{original}} \cdot \text{Embedding}_{\text{generated}}}$$

It is widely used in facial aging prediction research and works to improve generative models by incorporating visual accuracy into aging, for example, to avoid changes in eye shape or unrealistic forehead width. Its value ranges between (1 and -1), and the closer the value is to 1, the greater the similarity. It is characterized by its high flexibility towards age changes and provides a unified assessment that does not rely on human evaluation, focusing on the main features of the face.

VI. FUTURE DIRECTIONS

Future research efforts aspire to develop new algorithms and technologies that strike a harmonious balance between these competing goals. The dataset faces problems such as bias and lack of representation of certain age groups or ethnicities, which negatively affects the efficiency and effectiveness of facial aging models and their generalizability. Most studies were mainly based on facial images, we recommend combining multimedia data such as voice, text (such as medical records) and biosensor data such as heart rate, skin to enhance the accuracy of facial aging prediction models by collecting multimedia data from several sources such as (health institutions). Also taking advantage of competitive generative networks (GANs) in increasing generative data (Generative Data Augmentation) to create images with various signs of aging and under different conditions for the purpose of increasing training data and thus improving the performance of models.

In the future, it is best that future work in the field of facial aging focus on exploring generative models with improved interpretability, integrating field knowledge from fields such as psychology and aging, in addition to employing emerging technologies such as augmented reality (AR) and virtual reality (VR) to create more interactive and realistic facial aging experiences. By addressing these challenges and leveraging the latest research innovations, the field of facial age progression has enormous potential to achieve transformative progress with far-reaching societal impacts.

In addition to benefiting from and developing Continual Learning Models so that they can adapt to new data over time without the need for retraining from scratch, such as Learning without Forgetting techniques to maintain model performance and thus obtain more flexible and adaptable models with data over time. In addition to using Hybrid Machine Learning Techniques that combine Generative Adversarial Networks, deep learning, and reinforcement learning by developing an advanced model that combines these techniques to create images of aging faces and leveraging reinforcement learning to enhance prediction accuracy while improving performance in various conditions such as (expressions, lighting, angles).

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VII. CONCLUSION

In conclusion, facial aging prediction research is a vital and evolving field encompassing computer vision, machine learning, and ethics. As demonstrated by the methodologies discussed, ranging from traditional feature-based approaches to advanced deep learning techniques such as Generative Adversarial Networks (GANs) and hybrid methods, the complexity and diversity of approaches used contribute to the accurate prediction of the facial aging process. While each approach has its own advantages and innovative contributions, the quality and diversity of the dataset used in the training and evaluation process determine the success of these methodologies.

Ethical considerations related to data collection, specifically regarding the inclusion of children's images, require careful handling to ensure privacy and minimize potential effects. In addition, the comprehensive evaluation of the publicly available datasets presented here highlights the primary importance of the various data repositories detailed in supporting facial aging research.

It is expected that when applying hybrid models that combine Conditional GANs and Variational Auto encoders (VAEs) to improve the quality of generated images, because VAEs prepare initial representations based on conditional variables, we obtain realistic data, and for better accuracy and more realism, we use conditional GANs. Generalization problems can be overcome by training the model on larger and more diverse data. Computational efficiency can also be improved by using model compression techniques or energy-efficient training.

The application of augmented reality based on facial aging prediction techniques enhances the work of plastic surgeons by presenting the effects of aging more realistically, understanding changes based on the aging prediction system, and supporting plastic surgery decisions by giving them a better perception of how an individual's appearance changes during age. The overall performance of models can be improved using generative competitive networks (GANs), reinforcement learning, training robotics with high efficiency, and generating training environments that promote learning and adaptation. These technologies work together to create training data Complex Contributes to the Generative Potential of Models In the near future the integration of diverse disciplines and ethical awareness will be critical in harnessing the full potential of facial aging techniques to reap societal benefit while addressing related ethical concerns.

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REFERENCES

[1] I.K. Zaal and Y. F. Mohammad, “Machine Learning Algorithms for Human Smoking Behavior Detection using speech,” *in 2023 16th International Conference on Developments in eSystems Engineering (DeSE), IEEE*, 2023, pp. 298–302.

[2] P. K. Chandaliya and N. Nain, “AW-GAN: face aging and rejuvenation using attention with wavelet GAN,” *Neural Comput. Appl.*, vol. 35, no. 3, pp. 2811–2825, 2023.

[3] W. Yao, M. A. Farooq, J. Lemley, and P. Corcoran, “Synthetic Face Ageing: Evaluation, Analysis and Facilitation of Age-Robust Facial Recognition Algorithms,” *arXiv Prepr.* arXiv2406.06932, 2024.

[4] D. Deb, N. Nain, and A. K. Jain, “Longitudinal study of child face recognition,” *in 2018 International Conference on Biometrics (ICB), IEEE*, 2018, pp. 225–232.

[5] P. K. Chandaliya, A. Sinha, and N. Nain, “Childface: Gender aware child face aging,” *in 2020 International Conference of the Biometrics Special Interest Group (BIOSIG), IEEE*, 2020, pp. 1–5.

[6] J. Wahid, F. Zhan, P. Rao, and C. Theobalt, “DiffAge3D: Diffusion-based 3D-aware Face Aging,” *arXiv Prepr*. arXiv2408.15922, 2024.

[7] Q. Teng, R. Wang, X. Cui, P. Li, and Z. He, “Exploring 3D-aware lifespan face aging via disentangled shape-texture representations,” *in 2024 IEEE International Conference on Multimedia and Expo (ICME), IEEE*, 2024, pp. 1–6.

[8] H. Pranoto, Y. Heryadi, H. L. H. S. Warnars, and W. Budiharto, “Recent generative adversarial approach in face aging and dataset review,” *IEEE Access*, vol. 10, pp. 28693–28716, 2022.

[9] S. Li et al., “ID $^ 3$: Identity-Preserving-yet-Diversified Diffusion Models for Synthetic Face Recognition,” *arXiv Prepr*. arXiv2409.17576, 2024.

[10] S. Palsson, E. Agustsson, R. Timofte, and L. Van Gool, “Generative adversarial style transfer networks for face aging,” *in Proceedings of the IEEE conference on computer vision and pattern recognition workshops*, 2018, pp. 2084–2092.

[11] C. N. Duong et al., “Automatic face aging in videos via deep reinforcement learning,” *in Proceedings of the*

ISSN (online): 2581-3048
Volume 9, Issue 4, pp 33-49, April-2025
https://doi.org/10.47001/IRJIET/2025.904006

IEEE/CVF conference on computer vision and pattern recognition, 2019, pp. 10013–10022.

[12] G. Wu et al., "ACGAN: Age-compensated makeup transfer based on homologous continuity generative adversarial network model," *IET Comput. Vis.*, vol. 17, no. 5, pp. 537–548, 2023.

[13] I.Kemelmacher-Shlizerman, S. Suwajanakorn, and S. M. Seitz, "Illumination-aware age progression," *in Proceedings of the IEEE conference on computer vision and pattern recognition*, 2014, pp. 3334–3341.

[14] X. Shu, J. Tang, H. Lai, L. Liu, and S. Yan, "Personalized age progression with aging dictionary," *in Proceedings of the IEEE international conference on computer vision*, 2015, pp. 3970–3978.

[15] S. Yamamoto, P. A. Savkin, T. Kato, S. Furukawa, and S. Morishima, "Facial video age progression considering expression change," *in Proceedings of the Computer Graphics International Conference*, 2017, pp. 1–5.

[16] J. Tang, Z. Li, H. Lai, L. Zhang, and S. Yan, "Personalized age progression with bi-level aging dictionary learning," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 40, no. 4, pp. 905–917, 2017.

[17] A.Elmahmudi and H. Ugail, "A framework for facial age progression and regression using exemplar face templates," *Vis. Comput.*, vol. 37, no. 7, pp. 2023–2038, 2021.

[18] A.Sinha and S. Barde, "Face recognition across age progression by using PCA," *Int. J. Food Nutr. Sci.*, vol. 11, pp. 4608–4617, 2022.

[19] A.Sinha and S. Barde, "Age Invariant Face Recogntion Using Pca And Msvm," *J. Pharm. Negat. Results*, pp. 2174–2185, 2022.

[20] Z. Zhang, Y. Song, and H. Qi, "Age progression/regression by conditional adversarial autoencoder," *in Proceedings of the IEEE conference on computer vision and pattern recognition*, 2017, pp. 5810–5818.

[21] M. Ghayoumi, Generative Adversarial Networks in Practice. *CRC Press*, 2023.

[22] I.Goodfellow et al., "Generative adversarial networks," *Commun. ACM*, vol. 63, no. 11, pp. 139–144, 2020.

[23] D. P. Kingma and M. Welling, "Auto-encoding variational Bayes. CoRR, abs/1312.6114*," arXiv Prepr. arXiv1312*.6114, 2013.

[24] A.Makhzani, J. Shlens, N. Jaitly, I. Goodfellow, and B. Frey, "Adversarial autoencoders," *arXiv Prepr.* arXiv1511.05644, 2015.

[25] C. Shi, J. Zhang, Y. Yao, Y. Sun, H. Rao, and X. Shu, "CAN-GAN: Conditioned-attention normalized GAN for face age synthesis," *Pattern Recognit. Lett.*, vol. 138, pp. 520–526, 2020.

[26] N. Sharma, R. Sharma, and N. Jindal, "An improved technique for face age progression and enhanced super-resolution with generative adversarial networks," *Wirel. Pers. Commun.*, vol. 114, pp. 2215–2233, 2020.

[27] D. H. Krishna, S. Akshay, A. N. S. Manikumar, and D. H. Sukumar, "Age Vision: AI Powered Facial Age Progression Platform," 2024.

[28] H. A. Younis and Y. F. Mohammad, "Hybridization of Self Supervised Learning Models for Enhancing Automatic Arabic Speech Recognition," *in 2024 4th International Conference of Science and Information Technology in Smart Administration (ICSINTESA), IEEE*, 2024, pp. 650–655.

[29] H. A. Younis and Y. F. Mohammad, "Arabic Speech Recognition based on Self Supervised Learning," *in 2023 16th International Conference on Developments in eSystems Engineering (DeSE), IEEE*, 2023, pp. 528–533.

[30] Y. Hu, "Face Age Prediction Based on Machine Learning," *Highlights Sci. Eng. Technol.*, vol. 94, pp. 124–128, 2024.

[31] C. Shi, S. Zhao, K. Zhang, Y. Wang, and L. Liang, "Face-based age estimation using improved Swin Transformer with attention-based convolution," *Front. Neurosci.*, vol. 17, p. 1136934, 2023.

[32] W. An and G. Wu, "Hybrid spatial-channel attention mechanism for cross-age face recognition," *Electronics*, vol. 13, no. 7, p. 1257, 2024.

[33] M. A. Farooq, W. Yao, G. Costache, and P. Corcoran, "Childgan: large scale synthetic child facial data using domain adaptation in stylegan," *IEEE Access*, 2023.

[34] K. Ricanek Jr and T. Tesafaye, "MORPH: A longitudinal image Age-progression, of normal adult," *in Proc. 7th Int. Conf. Autom. Face Gesture Recognit*, 2006, pp. 0–4.

[35] K. Ricanek and T. Tesafaye, "Morph: A longitudinal image database of normal adult age-progression," *in 7th international conference on automatic face and gesture recognition (FGR06), IEEE*, 2006, pp. 341–345.

[36] G. Levi and T. Hassner, "Age and gender classification using convolutional neural networks*," in Proceedings of the IEEE conference on computer vision and pattern recognition workshops*, 2015, pp. 34–42.

[37] R. Rothe, R. Timofte, and L. Van Gool, "Deep expectation of real and apparent age from a single image without facial landmarks," *Int. J. Comput. Vis.*, vol. 126, no. 2, pp. 144–157, 2018.

[38] S. Moschoglou, A. Papaioannou, C. Sagonas, J. Deng, I. Kotsia, and S. Zafeiriou, "Agedb: the first manually collected, in-the-wild age database," *in proceedings of*

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https://doi.org/10.47001/IRJIET/2025.904006

the IEEE conference on computer vision and pattern recognition workshops, 2017, pp. 51–59.

[39] A.Zargaran, S. Sousi, S. P. Glynou, H. Mortada, D. Zargaran, and A. Mosahebi, "A systematic review of generative adversarial networks (GANs) in plastic surgery," *J. Plast. Reconstr. Aesthetic Surg.*, vol. 95, pp. 377–385, 2024.

[40] C. Li, Y. Li, Z. Weng, X. Lei, and G. Yang, "Face aging with feature-guide conditional generative adversarial network," *Electronics*, vol. 12, no. 9, p. 2095, 2023.

[41] N. A. Sultan and R. P. Qasha, "CONTAINER-BASED VIRTUALIZATION FOR BLOCKCHAIN TECHNOLOGY: A SURVEY.," *Jordanian J. Comput. Inf. Technol.*, vol. 9, no. 3, 2023.

[42] H. E. Solayman and R. P. Qasha, "On the use of container-based virtualisation for IoT provisioning and orchestration: a survey," *Int. J. Comput. Sci. Math.*, vol. 18, no. 4, pp. 299–311, 2023.

[43] Y. Galphat, C. Bajaj, G. Amarnani, K. Mulchandani, and J. Repale, "Exploring Techniques For Age Progression In Facial Images: A Comprehensive Survey," *J. Syst. Eng. Electron. (ISSN NO 1671-1793)*, vol. 34, no. 5, 2024.

[44] S. Shen, X. Yuan, J. Wang, L. Fan, J. Zhao, and J. Tao, "Evaluation of a machine learning algorithms for predicting the dental age of adolescent based on different preprocessing methods," *Front. Public Heal.*, vol. 10, p. 1068253, 2022.

[45] M. Suin, N. G. Nair, C. P. Lau, V. M. Patel, and R. Chellappa, "Diffuse and restore: A region-adaptive diffusion model for identity-preserving blind face restoration," *in Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, 2024, pp. 6343–6352.

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