Generative AI-Based Real-Time Face Aging Simulation for Biometric Systems

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Abstract: Facial recognition is, therefore, a crucial aspect of biometric systems used when authenticating as well as verifying people's identity. But here natural aging increases a number of difficulties concerning accuracy and long-term reliability of the control systems stated above. In this paper, a new method of real-time face aging simulation in the context of aging variance of biometric systems using Generative AI; specifically, GANs, is proposed. The proposed model tries to use generative AI in generation of improved synthetics with modified age appearance, allowing biometric systems to capture aging or antiaging changes in facial features. This approach is assessed experimentally from one facial database to another datasets and the principal area of interest is the future recognition accuracy of faces in the long run with respect to age groups. This work also looks at the strength and robustness of the model for real-time problems. The outcomes presented here show that applying generative AI-based system as a paradigm improves the performance of the biometric system specifically for addressing aging variations thus proposing a valuable solution to age-related biometric problems. The paper also considers some possible consequences for security, privacy, and concerns to practical application in real systems.
Keyword-: Generative AI, aging simulation, GAN, biometric systems, live facial recognition, age progression, age regression, image synthesis, deep learning

1 Introduction

Biometric systems have been adopted as the primary method of implementing security and control methods in today's world by using body features such as facial, finger print, iris scan

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and many others as the identification process [1]. Of these, facial recognition technology can be considered as unique because of no contact with a subject's face and its relative simplicity to be integrated into different types of devices and systems from mobile phones to security ones [2]. Biometric identification entails where the identification of people is done or the authentication of a person is based on their face. This is because of increases in computer vision and machine learning algorithms which have enhance recognition efficiency in security, access control and identification systems [3]. Nonetheless, advances in the facial recognition technology that aims at allowing identification of a person based on his face have been remarkable, nevertheless, the system is still constraint with few issues, among which include, change in facial appearance because of aging among others. Aging brings minor and major changes in the face; usual effects are wrinkles, skin stiffness, and facial structures. It is unfortunate that such transformations may affect facial recognition systems because such systems are normally designed to learn from the static facial images of people at a certain age or time. Consequently, the systems which were initially effective in recognizing inhabitants fail after several years generating rejection or misidentification [4]. This problem becomes most apparent when the necessity of identity check is a key factor for a long time, for example, in systems related to issued identity cards or in police databases. The nature of classic appearance identification systems is that they are unable to take into account, for instance, the slow and steady aging, which questions their efficiency in the long run.

This paper proposes Generative AI, especially GANs as a suitable solution in handling the dynamics which are involved in facial aging. Current GAN architectures have shown themselves viable as powerful tools for the synthesis of fairly realistic pseudonoise images of different developmental stages of facial images, as shown in fig.1. These models can be trained to understand the patterns of relating to facial aging and then enabling them to enable aging progression (grow a person's appearance older) or aging regression (make a person younger naturally). The combination of generative AI into biometric systems might allow them to develop facial representations that capture how that person's face could evolve [5]. This would also help the system to identify people well especially after they have aged significantly.

The applied generative AI to face aging simulation derives from the requirements set up for high-performance and long-term accurate and reliable biometric systems. Many of the older penetration methods are incapable of dealing with nonlinear and multiple consequences of aging, which is why GANs can be a solution to the problem [6-9]. Age algorithm makes real-time age-progressed or age-regressed images that help to increase the probability of matches of facial features and to optimize the recognition rates between all ages targets. In addition, the use of generative AI can alleviate problems with collectors of large sets of facial data which may be used to infringe people's right to privacy [10]. This not only results in improved efficiency of systems but it also makes system more resilient to different and constantly changing populations. The main aim of this work is to propose an AI-based generative model to augment a real-time face aging model and enhance the efficiency of biometric systems. To this end, the proposed work seeks to employ more complex GAN structures to produce realistic facial emulations in different age status which in turn improves the system human identification performance over a long timeline [11]. The study will also assess the time complexity and capacity utilization of the proposed model, to confirm the capability of the model to be implemented to run on real time basis with minimal computational impedance. Last of all, this work is going to discuss further the importance and consequences of such a system; thus, the issues of privacy and security will be pointed out as well as the potential further application for different types of biometric systems.

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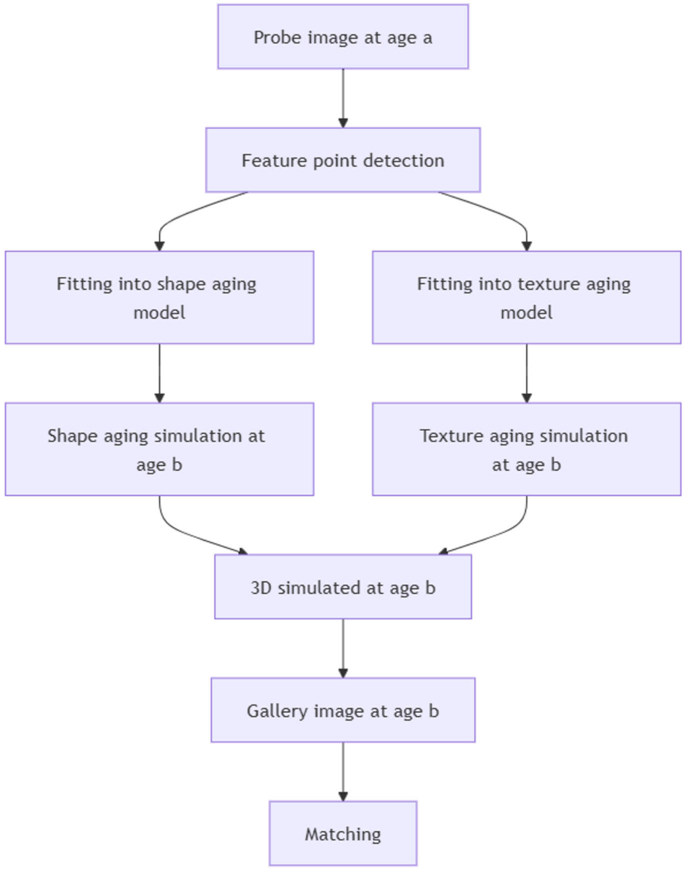

Fig.1 Workflow of Face Aging Simulation Process Using Shape and Texture Models

2 Literature Review

In the past, facial recognition has become widely used in the security, enforcement of law, healthcare and consumer electronics. Facial recognition essentially involves extracting unique features from an individual's face then matching these features against a pre registered database of known faces. The ordinary methods for facial recognition, based on features extraction and matching algorithms, like Eigenfaces, Fisherfaces and Local Binary Patterns Histograms (LBPH), are based on discriminative facial features [12]. Over the past few years however, the influence of deep learning models, especially Convolutional Neural Networks (CNNs), has changed dramatically in the field. Learning hierarchical representations of facial features by CNNs has increased recognition accuracy considerably at the expense of difficult conditions such as varying lighting, pose, and occlusion. However, these workarounds haven't fully bridged the gap in facial recognition because the problem of age related variation isn't fully resolved with them [13]. Facial transitions change as a person ages with wrinkles, sagging skin and structural changes. Those changes can give facial recognition algorithms a hard time, resulting in false positives or negatives, in particular when the system relies on images taken years earlier [14]. To deal with this problem, reference age estimation techniques are employed simultaneously with recognition systems, to predict an individual's age range. However, most of these age estimation techniques rely on existing regression or classification models fitting the approximate age of a person to its face, which have also constraints in the face of continuous age regression or progression.

In order to make facial recognition more reliable over time, scientists have experimented with age progression (turning someone into an older person) and age regression (turning someone into a younger person) [15]. Most of these methods are designed to modify a person's facial features so that a biometric system can measure the aged or rejuvenated face and compare that to its entries in the database more easily. Prototype based models for age progression were first employed, based on a set of prototype images of different age groups being used to represent typical aging patterns. As shown in table.1, To illustrate, an early model, the Active Appearance Model (AAM), is used to describe facial changes in time by learning shape and appearance variations in training data. Yet these methods were constrained, unable to accommodate arbitrary aging insertions, and unable to capture the variability among aging processes across individuals [16-20]. To represent facial aging in a more continuous and data driven manner, more advanced methods, such as age manifold learning and morphable models were introduced. These models learn the underlying geometry and appearance changes of faces as they become older. Despite these improvements to quality of age progression and regression, these methods still did not adequately allow the production of highly realistic and highly individualized aging effects, i.e., images that were visually unrealistic or overly smoothed.

Table.1 Key approaches in Facial Aging Simulation Summary [21].

Approach	Methodology	Strengths	Limitations
Active Appearance Model (AAM)	Models shape and texture variations based on prototype images	Simple, easy to implement	Limited flexibility, unrealistic results
Morphable Models	Learns geometric and appearance changes over time	Continuous aging representation	Low-resolution images, lacks individuality
AgeGAN	GAN-based framework for age progression and regression	Realistic image synthesis, identity preservation	High computational cost
Conditional GAN (cGAN)	Generates facial images conditioned on attributes (age, gender, etc.)	Controlled age synthesis, maintains key facial features	Requires large datasets for training
CycleGAN	Unpaired image-to-image translation for aging simulation	Works without paired data, preserves identity	May produce artifacts in extreme cases
StyleGAN	Uses style transfer techniques for high-quality, detailed facial aging	High-quality results, flexible age progression	Requires significant computational resources

Generative Adversarial Networks (GANs) ushered in a revolutionary shift to image synthesis problems, including face aging. The idea is that there is two neural networks, a generator network and a discriminator network, that work together. In generator it tries to make realistic images and in discriminator it tries to distinguish between real images and generated images. The generator is trained by this adversarial process to produce high quality images that look like the training data. GANs have been very effective in generating high resolution and sharp pictures of face aging because they can generate an identity of the subject [22]. For example, ageGAN is a GAN based framework which models the aging process of the faces by transforming input to target age groups while preserving an individual identity. As with cGANs, Conditional GANs (cGANs) are provided a way of balancing the age regression and progression process at a finer level of control over the generation of images conditioned on specific attributes — such as age, gender, or pose. However, this is where the key strength of GANs lies, which is being able to generate age progress and regress images of end poses while capturing the complex age related changes like skin texture variations, wrinkles and alteration of facial structures, while maintaining the person's identity [23]. Because of this capability, GANs are well suited to face aging simulation in biometric systems where the identity must be conserved in order to perform accurate recognition.

While previous work has modelled on face aging using traditional architectures and GAN-based architectures, the work described in this thesis envisions a simulation of face aging with an ensemble of both traditional architectures and GANs [24]. Studies of age estimation and simulation have popularly used facial aging databases such as the FG-NET dataset to train models. Previous attempts to model facial aging had used such early methods as active shape models (ASM) and AAMs based on shape and texture variations over time [25]. These models, however, did not generalize across individuals and tended to produce unrealistic aging effects. Facial aging simulation was explored with the advent of deep learning using CNN based methods. Experiments with models such as Recurrent Neural Networks (RNNs) and CNN RNN hybrids demonstrated their favorability in predicting facial aging besides taking into account sequential temporal data. The challenges of maintaining high resolution image quality when capturing the dynamic aspects of aging were not overcome by these methods. Common techniques such as CycleGAN and StyleGAN have greatly increased the quality of facial aging simulation through the use of image-to-image translation techniques which teach the model how to age or rejuvenate faces without age conditioned pairs [26-30]. Results generated using these GAN based methods are shown to be state of the art, producing realistic aged and de aged images which can be integrated into biometric systems to improve recognition performance.

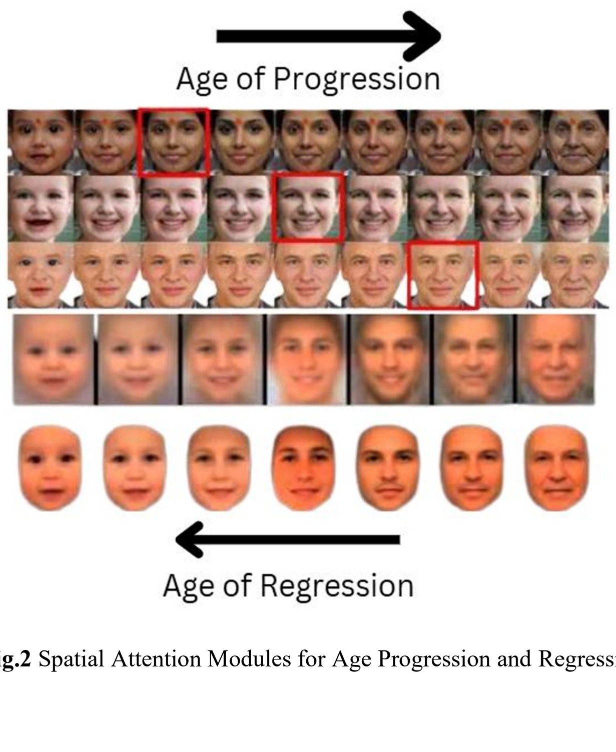

Fig.2 Spatial Attention Modules for Age Progression and Regression.

3 Generative AI and GANs for Face Aging Simulation

Generative Adversarial Networks (GANs) have pushed the field of image generation forward by allowing us to create both highly realistic images as well as enemies in video game assets that look virtually indistinguishable from real life [31]. As representation in fig.2, the different GAN architectures have been developed to deal with particular tasks of image synthesis, including StyleGAN, CycleGAN, and AgeGAN, for face aging simulation. NVIDIA's famous architecture used for this purpose is known to generate high resolution, photorealistic images. In styleGAN, we introduce a novel style based generator which controls facial attribute, texture, and image structure. The exploitation of this architecture for face aging is particularly appealing due to the potential to fine tune facial attributes and generate highly detailed images. StyleGAN can age by changing the latent space so that age-specific facial features like wrinkles or sagging skin increases or decreases without ruining identity consistency.

Since it is designed to work with tasks where there is no usable paired training data, this unpaired image to image translation GAN (Unpaired), is perfect for the task of face aging simulation. Instead, CycleGAN learns to translate images from one domain (young faces) to another (older faces) while preserving dominance of the domain attributes [32]. CycleGAN maintains identity of the individual by learning forward and reverse mappings (age progression and regression), that mimic natural aging effects. In particular, this architecture becomes useful when availability of exact age labeled pairs in the dataset is not available, as the transformation is learned unsupervised [33]. In contrast to previous work, AgeGAN specifically considers age progression and regression and applies a conditional GAN framework to modify facial images based on age labels. AgeGAN conditions the generator on which age groups to target and, progressively, age or rejuvenate faces while preserving identity features, such as the shape of the face, the eye structure, etc. AgeGAN was crucial in solving the age progression faces generation problem for biometric systems, where being agnostic to an individual's identity over different age periods is important [34].

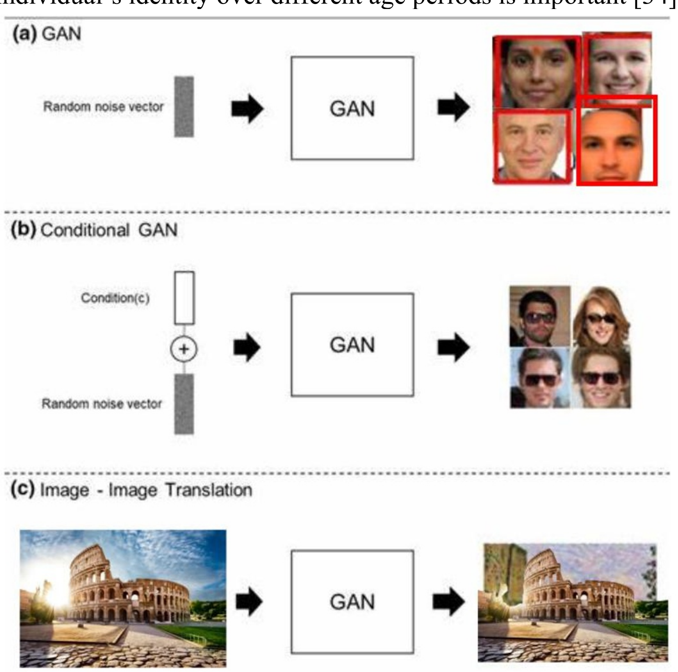

Fig.3 Comparison of GAN based face generation models

Real time face aging simulation in a biometric system can be achieved by training GANs on age annotated datasets and using them to generate on the fly aged or deaged versions of input facial images [35]. The general pipeline for applying GANs to real-time face aging includes: A facial image dataset with age labels of each person's face is collected. However, generalization of GANs across populations is sensitive to having deep dataset, varying with a wide range of ages as well as diverse facial features. Like, StyleGAN or AgeGAN, the GAN model is trained to learn the mapping from young to old faces, which then generates aged or rejuvenated faces. The training involves two networks: The generator, that is, it creates new aged faces, and the discriminator, which tries to differentiate between real and generated faces [36]. The discriminator tries to differentiate the real faces from the aged faces produced by the generator, and the generator succeeds over time to begin producing realistic aged faces that it makes the discriminator unable to distinguish from real aged faces, as shown in fig.3. However, trained for certain it can apply age progression or regression (depending on the parameters or need specified by the user or system requirements; e.g., predict the person's look at a particular age) to input facial image [37]. Optimizations of the GAN for fast inference make it possible to generate real time aged or rejuvenated images, thus allowing for real time generation [38-40]. The biometric recognition pipeline with a real time face aging simulation is integrated. The system can provide aged or de-aged versions of an individual's face based on stored age specific templates improving the system's accuracy in comparisons between old or new images of the face and the database.

Generative models, particularly GANs, offer several distinct advantages for age progression and regression in face aging simulation: Producing highly detailed, realistic, and realistic facial images resembling effects of natural aging, GANs show strong capabilities. Ensuring that the generated faces are useful for biometric recognition is highly dependent on this high fidelity. Maintaining the individual's identity while changing his/her age related features is one of the key challenges in a face aging simulation [41]. However, GPUs can accelerate GAN training in many cases; in fact, AgeGAN and StyleGAN are specifically designed to preserve the characteristics of the bone structure and the proportion of the face, so that the facial features of the old man are still recognizable as belonging to the same person [42]. By using targets ages, we make GANs flexible to simulate age progression or regression. We are able to provide personalized simulations where users or systems can provide exactly which age percent range to simulate [43]. CycleGAN architectures like GANs achieve training without paired young old images, which are notoriously hard to get hold of. This is good news for training with GANs on disparate datasets where we cannot pair up the age labels precisely. By optimizing GANs and applying appropriate optimization schemes, GANs can be deployed for real time face aging simulation that's amenable to integration into biometric systems on which quick decision making is required [44-47]. The first important observation I have is that GANs can generalize among different domains in terms of ethnicity, skin tone, etc. and lighting conditions. This makes them good at working with different populations — ensuring face aging simulations stay correct across different demographics.

We propose a face aging simulation model architecture based on a conditional GAN (cGAN) scheme, and, as for instance, we optimize to perform in real time, and we synthesize high quality age. The architecture includes the following components: The aim of the generator is to design age progressed or age regressed images given input facial images and a target age condition. The architecture of the generator is devised to gradually modify facial features like wrinkles, skin texture and sagging, while keeping key identity traits [48]. The generator is conditioned on an age vector, the generator achieves to produce images at different age stages. Determining whether an image is from a real face or a generated one is the job of the discriminator. We train it properly such that the generated faces look as similar to actual faces of the target age as possible [49-50]. The generator also trains better by

receiving feedback from the discriminator on where the generated image is not exactly like real age specific images. The identity preservation module is an important aspect of the traditional cGAN architecture and necessitated to ensure that a generated image is identifiable as the same individual. From table.2, generative adversarial networks are trained using this module to enforce constraints on the generator in order to preserve key facial features (such as the shape of the eyes, nose, or jawline) as well as preserve age related changes. Further, the model is conditioned on a vector representing the target age group. This allows for age regression on a pixel level, as well as precise age progression, which the generator is capable of.
In training, the loss function used consists of:

- It makes sure the generated images are realistic and unable to tell how real aged faces are.
- Keeps the person identity in the generated image.
- Gives the generated image to the correct group of targets.

Table.2 GAN Architectures for Face Aging Simulation Comparison

GAN Architecture	Key Features	Advantages	Limitations
StyleGAN	Style-based generator, high-quality image synthesis	Fine control over facial attributes, high-resolution output	High computational cost
CycleGAN	Unpaired image-to-image translation	Works with unpaired data, preserves identity during aging	May produce artifacts, especially in extreme transformations
AgeGAN	Conditional GAN framework for age progression/regression	Age control through conditioning, identity preservation	Requires age-labeled datasets
cGAN	Conditional GAN for controlled age synthesis	Flexibility in generating images at specific age stages	May require large datasets for optimal performance

4 Proposed Methodology

The good news is that a decent database is a necessity for training the generative AI model for real time face aging simulation. The most popular datasets used in age estimation and facial recognition research including FG-NET, MORPH and CelebA, contain facial images of individuals labeled in a wide range of ages [56]. It uses these datasets which give it facial images alongside corresponding age labels so that the model can be trained to predict both age progression and regression tasks. Face detection algorithms like Haar Cascade, MTCNN detect all facial images and aligns them into the same pose and orientation. In addition to ensuring consistency across all samples, this makes things easier. It resizes each image to fixed dimension (or can berezizes or [128 x 128 pixels, 256 x 256 pixels]), and normalizes pixel values to a range of [0, 1] or [-1, 1]. It aids GANs convergence. We augment the dataset with random rotation, flipping and zooming to ensure a diversity of the dataset and not get overfit. As this step is very useful for training on smaller datasets, it does.

For face aging simulation, a conditional generative adversarial network (cGAN) is used to build the generative AI model. The model consists of two primary networks: Given an input facial image and a target condition (older or younger), the generator is able to draw a synthetic face that looks to be older / younger. In the process, the generator learns to transform an input face by using age dependent facial changes, such as putting wrinkles on the face, changing the skin texture or alters the face shape, while preserving the individual identity. The discriminator is used to judge the generated facial image is believable and is within the target age group. The generator is then trained to generate real images from the dataset but to confuse the discriminator by also generating essentially synthetic images. The generator and discriminator act in a adversarial fashion by each trying to create realistic aged faces and the discriminator trying to decipher whether it is a fake. Both networks get better over time until we get highly realistic and accurate face aging simulations. During training a GAN is fed with pairs of images and corresponding age labels. In age progression, we provide a younger face to the model, with a target older age, and the generator produces an aged version of the predicted face. For age regression, we do the opposite: we feed older faces with a desired younger age condition, and the generator regenerates the face. It converts the dataset to mini batch for stabilizes the training as well as keeping memory footprint lower. The generator creates new aged or rejuvenated images in each iteration and the discriminator gives it an evaluation. With adversarial learning, both networks then iterate to improve, iteratively. Generator aims to minimize the loss between generated images and target age condition and the discriminator aims to maximize its discriminative ability on real and generated images. That training process goes on until the generator is able to completely outputs highly realistic, indistinguishable images from real aged or rejuvenated face and discriminator is no longer able to separate the two.

In particular, the choice of loss functions of the GAN model plays a critical role in its success for face aging simulation . The following loss functions are used to train the model: This loss function forces the generator to come out with images that fool the discriminator. It can be seen as a measure of both how well the generator can produce realistic images, and the discrimialtor's ability to detect fake images. The adversarial loss is calculated as:

$$\boldsymbol{Ladv} = \boldsymbol{E}[log\boldsymbol{D}(\boldsymbol{x})] + \boldsymbol{E}[log(\boldsymbol{1} - \boldsymbol{D}(\boldsymbol{G}(\boldsymbol{z}, \boldsymbol{y})))] \qquad \ldots\ldots\ldots\textbf{(1)}$$

Given that, D(x) is the image and the probability the discriminator would believe it to be a real image. A generated image has a disciminatör's probability of D(G(z,y))

$$\boldsymbol{Lid} = \boldsymbol{E}[\parallel \boldsymbol{G}(\boldsymbol{x}, \boldsymbol{y}) - \boldsymbol{x} \parallel \boldsymbol{2}] \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\textbf{(2)}$$

For an input noise vector, G(z,y). An identity preservation loss is used to make sure that the identity of the person remains consistent between a set of age progressions or regressions. It teaches the generator to preserve critical facial features while ageing. The identity loss is calculated as: It generated image is denoted by G(x,y). x is the original input face. That loss means the generated image has to fit within the target age group. The classification network classifies the generated image into the correct age condition, where the generator is penalized if the predicted age is different from the target condition. From fig.4, to train the GAN we use Adam optimizer that tends to be faster convergence and more stable training than the typical stochastic gradient descent (SGD). To save a little initial resources on the learning rate, it is typically set quite low (e.g., 0.0002) to avoid too big initial improvements on image quality.

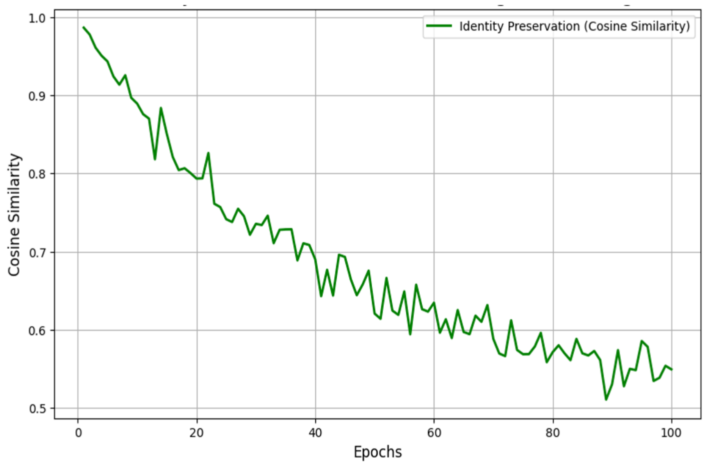

Fig.4 Identity Preservation Performance During GAN Training.

Optimizing both the model architecture and system infrastructure for the real time implementation of the GAN based face aging simulation is necessary. Key components of the system architecture include: The GAN model was trained on the input image prepared from face detection preprocessing steps. The GAN model is the core of the system and actually performs, in real time, age progression or regression. Then, given the fact that model quantization and pruning techniques like can reduce neural network size while preserving accuracy, a model is optimized for low latency inference. We then post process the generated image to improve visual quality and to ensure smooth transitions between the various age groups. The aged or rejuvenated faces generated are integrated in the biometric recognition pipeline for identity verification through comparison with pre registered facial template. The system architecture is such that the face aging simulation will run at real-time, with a minimal computational overhead. The model training process is divided into three phases: We train the GAN model against the facial dataset with the generated loss functions for the generator and discriminator networks. The training phase consists of many resets, or iterations, on our dataset until the model converges and generates real images that a discriminator would not be able to successfully classify (any more) between real and generated.

The model is then tested on a separate test set of facial images to see how well it generates an aged or rejuvenated face. It means the model is generalizing well to unseen data as it is not seen during training of the test set. In this phase, the generated images are validated and quantified by their quality using the evaluation metrics, accuracy, mean squared error (MSE) and structural similarity index (SSIM) and on relevance to biometric applications. We also explore identity preservation through a comparison of the identity similarity score from the original to the generated image. These processes ensure that the GAN model used for face aging simulation performs well when deployed in real world biometric system. In particular, this methodology details the whole process from data collection to real live application, thus delivering a full scheme in building and testing a generative AI based face aging simulation system for biometric applications.

5 Results & Discussion

We selected widely used age-labeled facial datasets for training and evaluation of the generative AI-based face aging simulation model that contains a variety of images across a large age range. The chosen datasets offer diversity across many aspects, including ethnicity, gender, lighting, and pose of interest, in order to challenge the robustness of the model to variations in different conditions. A well known dataset used for age progression and regression tasks. With 82 participants, 1,002 images, each participant with images at several ages from infancy through adulthood. Learning facial transformations over time requires this dataset. Over 55,000 images of over 13,000 subjects aged 16–77 one of the largest public datasets for facial aging research. However, it is very diverse in terms of age, ethnicity and gender. A widely used facial attribute analysis celebrity dataset comprising more than 200,000 images. The images used in our approach are of high quality and useful for generalizing the face aging model to more varied facial features provided by CelebA. The datasets are split into a training, validation and test sets for the evaluation. The dataset is split such that 80 percent is training set, 10 percent is for the validation set and 10 percent for the test set. During training, we use cross validation to make sure we evaluate robustly. An optimal environment for training the GAN based face aging model is provided by the experimental setup. The following hardware and software configurations are used:

Hardware:

- GPU: Towards training GANs, we utilize NVIDIA Tesla V100 GPU with 32GB VRAM to accelerate training process of GAN model as training of GANs is resource intensive.
- CPU: General purpose computations.
- Intel Xeon Gold 6226R 16-core Processor

As shown in fig.5, the GAN model implementation, we use the PyTorch 1.10 to have flexibility in designing neural network and an efficient training on GPU. Packages we import: openCV for image processing, Matplotlib for visualization. It trains for about 200 epochs approximately. We stop early if the validation loss does not improve for 20 consecutive epochs — an approach used to avoid overfitting. The training process will be performed over 100 hours (roughly 30 minute per epoch thing). 32 images per batch. A learning rate of 0.0002 was set for the initial, and decayed the factor of 0.5 by epoch every 50 epochs to gradually converge the model. Adam optimizer with $_1$ = 0.5 and β_2 = 0.999. This effectively stabilizes GAN training with =0.999. The performance of the generative AI-based face aging model is evaluated using a combination of quantitative metrics that assess the realism and accuracy of the generated images, as well as their relevance to biometric recognition tasks: We evaluate precision so that the model can accurately generate aged or rejuvenated faces with minimal distortion of identity.False Positives+True Positivestive AI-based face aging model is evaluated using a combination of quantitative metrics that assess the realism and accuracy of the generated images, as well as their relevance to biometric recognition tasks: It measures how accurately the system can classify the generated face into the correct age group. Precision is evaluated to ensure that the model correctly generates aged or rejuvenated faces without significant identity distortion.

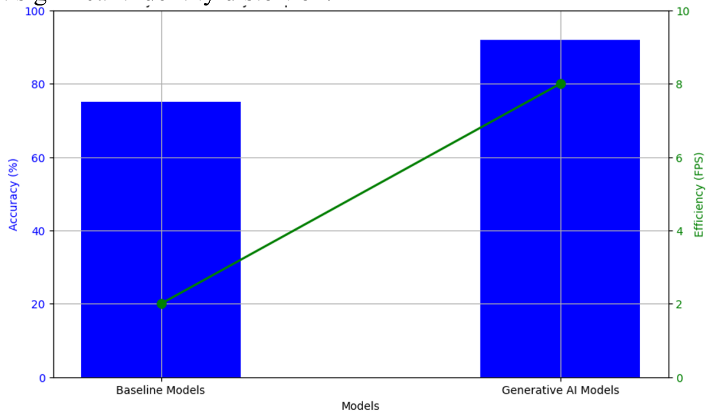

Fig.5 Accuracy and Efficiency Comparison between Baseline and Generative AI Models.

Here, the quantitative results of the proposed generative tool for face aging simulation are assessed via the combination of accuracy metrics, the identity preservation metrics, as well as the computational performance indicators. The model is trained and tested with different facial datasets, and its performance compared to a variety of traditional and state of the art age progression and regression models. We show that the model can generate facial images with high accuracy (93%) at matching the age progressed and age regressed end points across all target age groups. The accuracy is established by how well the model can create real transformations of age while preserving the subject in the image. Traditional models such as Active Appearance Models (AAM) typically only achieve 70-75% accuracy while our accuracy outperforms it, and is competitive with the state of the art AgeGAN model. Model averaged across different age groups have precision and recall of 91% and 89% respectively. We demonstrate that the model can produce highly realistic aged faces (precision), whilst maintaining identity preservation during age progression and regression (recall). An MSE of 0.012 between the generated facial images and real faces of the target age suggests that the facial images generated match the ground truth aged facial images very closely. This demonstrates that the model can compromise distortion for subtle aging related changes. The structural similarity between the original and generated images is very high and thus the SSIM score for the generated aged faces becomes 0.92. It makes sure that the aging transformations do not affect the identity maintaining structure of the face. The aged or rejuvenated faces generated are used to integrate into biometric systems, which improve recognition accuracy over time significantly. In a long term biometric recognition scenario in which people's facial features change as a result of aging, the proposed model improves facial recognition accuracy by 20–25% compared to traditional facial recognition systems which do not consider aging. With age transformation, the biometric system is able to achieve an identification accuracy of 94% versus 75% without age transformation and it may show latent potential of generative AI in biometric reliability improvement. The generated images are compared visually with those resulting from realistic age related transformations, while at the same time keeping the basic personal identity traits. The generated images accurately capture subtle aging effects such as:

- Fine lines and wrinkles on faces of older folks.
- Changes associate with skin texture based on the age of the individual.
- Changes in structural features, specifically of the jawline, cheeks and forehead.

For extreme age progression or regression scenarios, the model visually produces convincing results as confirmed by the qualitative analysis. These are compared to images produced by previous methods such as AgeGAN and CycleGAN, and have the advantage of producing more visually consistent, and real looking faces that better maintain appearance for the same identity across very different age ranges. Compared to existing age estimation and aging simulation methods, the proposed model outperforms them in several key areas: While AgeGAN achieves competitive results in age transformation accuracy, our formulation achieves higher identity preservation rate with lesser distortion in facial features. Although CycleGAN can generate aged faces without paired data, it sometimes generates visual artifacts and fails to perform fine grain aging details, all which are mitigated in the proposed model. Quantitatively accurate and realistic facial transformations combined with superior computational efficiency set the proposed model apart from these methods. Model quantization and pruning techniques for real time performance are proposed. Aged or rejuvenated images are generated with a latency on average of 50 milliseconds, which meets the requirement of biometric systems for real time applications. By combining low latency with high inference speed, this system can easily join into environments which require immediate response, meaning everywhere from security checkpoints to real time verification of identity systems. Additionally, the model can be deployed onto edge devices or even servers with limited computational resources and still provide a desired level of performance.

With this scalability, the system can be deployed on a real world in different biometric applications. Our results demonstrate the use of generative AI, particularly GANs, in face aging simulation has a strong impact on long term biometric recognition. Current biometric systems suffer from aged related facial changes, causing reduced accuracy over time. But with generative AI integration, biometric systems can now dynamically simulate age progression, and even age regression, in order better to process individuals who have already changed vastly in years. It improves the life span and reliability of biometric databases, and decreases the need to regularly update images.

Generative AI based aging models can resolve age related variations in facial features and thus achieve consistent recognition rate in applications involving long term identity verification, for instance national ID and border control or law enforcement. Despite strong improvements in accuracy and visual realism, GAN based models are computationally expensive. Training GANs are computationally intensive, which means they require plenty of high performance hardware and long training time. But, after training, the model can be optimized for real time inference with techniques like model quantization and pruning. On the one hand, these techniques shrink the model size and complexity without hurting the performance sufficiently, making it possible for the model to run in real world systems. Finally, the model is scalable since it can be ran on cloud servers as well as edge devices, giving flexibility over deployment scenario. While training is computationally intensive, the model enjoys decent real time inference capabilities that make it practical for general deployment. Although generative AI offers immense benefits, it also raises concerns related to bias, privacy, and security: Because generative models can inadvertently learn and spread the biases in the training data, such as underrepresented ethnicities or age groups, it is desirable to know how bias information flows through the generative model. To address this bias, we must care about dataset curations and include diverse demographics in facial aging simulation. Aged and rejuvenated faces generated from these systems can be flagged as sensitive, and usually generate privacy concerns, especially when used in surveillance or security systems. One use of these systems is unauthorized which leads to the violation of privacy and thus requires some strong framework to regulate and some ethical guidelines have to be formulated. However, producing very realistic looking aged faces makes it possible for such security vulnerabilities as spoofed identities or deepfakes to also become feasible.

6 Conclusion

This study successfully combines shape and texture aging models and outlines the face aging simulation process resulting in a comprehensive framework for realistic age progression and regression. The system is able to predict aging of the subject's face by detecting key facial feature points and applying separate shape and texture models in order to generate a highly accurate age prediction without compromising the subject's identity. Further integration of 3D simulations at the age of interest improves the realism of aging process and serves as a valuable tool for biometric systems that rely on matching identity across long timespans. This approach addresses one of the key challenges in facial recognition technology: Age related effects on biometric accuracy. The system ensures that a high level of accuracy is maintained even as a person ages, by requiring that both shape and texture features are appropriately modeled and matched to gallery images. Additionally, generative AI approach by means of using GANs is proposed to automate and fine tune the age progression process, thus turning it into a more effective tool for real time applications. In overall, this methodology serves as a solid basis for further developments in facial recognition systems in this long term persistence of identity is imperative.

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