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# REAL TIME FACE AGING PROGRESSION USING GAN's

**K. Jairam[1], SK. Sabeena[2], G. Tejaswi[3], M. Harika[4], K. VenkataYaswanth[5]**

*[1] Assistant Professor, Students[2,3, 4, 5], Department of computer Science and Engineering, SRK Institute of Technology, NTR, Andhra Pradesh, India*

**ABSTRACT**

In recent years, there has been significant rise in the recognition and adaption of Artificial Intelligence and Machine Learning. Now A days Face age progression is becoming a widely used technique in the modern era as it serves numerous applications. Real-time face aging progression using Generative Adversarial Networks (GANs) is an advanced deep learning approach that enables the realistic simulation of facial aging and rejuvenation. Unlike traditional image processing methods, GANs ensure photorealistic results by synthesizing fine-grained details such as wrinkles, skin texture, and facial shape variations. The proposed system can be applied in various fields, including forensics, entertainment, and digital personalization. By implementing real-time processing approach, which ensures instant and seamless age transformation, making it suitable for interactive applications. The integration of advanced deep learning techniques, such as attention mechanisms and progressive training, further enhances accuracy and realism. This study explores the potential of GAN-based face aging progression, highlighting its effectiveness in generating lifelike aging transformations while addressing challenges such as identity preservation and dataset biases. In our project, we will explore and implement face progression over different ages. We will use some frameworks, Libraries in Deep Learning Networks and Python to implement our application. Using Generative Adversarial Networks, we seek to generate older versions of oneself while preserving the identity of the individual. Using Generative Adversarial Networks, we seek to generate older versions of oneself while preserving the identity of the individual.

**Key Words**: Face Aging, Generative Adversarial Networks (GAN), Real Time Image Processing, Age Progression, Deep Learning, Computer Vision, Open CV, Face Generation, Generator, Discriminator, Image Generation, Face Detection.

## INTRODUCTION

Face aging progression is a critical area of research in computer vision and deep learning, with applications spanning forensic investigations, digital entertainment, healthcare, and social media. The conventional way of learning is mostly fragmented materials and no systematic direction, making it difficult to guide the learners in their career paths. Generative Adversarial Networks (GANs) are a class of deep learning models introduced by Ian Goodfellow in 2014. GANs consist of two neural networks, the generator and the discriminator trained in an adversarial manner. The generator aims to create realistic images, while the discriminator distinguishes between real and generated images. Unlike traditional computer vision methods, GAN-based face aging does not require explicit feature engineering or handcrafted rules. Instead, it learns the patterns of aging directly from large-scale datasets, ensuring high fidelity and realistic age transformations. One of the primary challenges in face aging progression is preserving the identity of the individual while applying age-related modifications. A successful face aging model should be able to generate images that accurately depict how an individual's face would change over time without introducing artifacts or altering key facial characteristics GAN architectures such as Progressive Growing of GANs (PG-GAN), Star GAN, and StyleGAN, real-time face aging models can generate high-resolution aged faces in a fraction of a second. GANs address limitations by learning the underlying patterns of aging directly from a dataset, and identity features while incorporating realistic aging effects such as wrinkles, facial structure changes, and skin texture variations.

## LITERATURE REVIEW:

Ramanathan and Chellappa [1] introduced *"Modeling Age Progression in Young Faces"*, which applied statistical shape and texture modeling based on craniofacial growth patterns. Though limited in realism, their work laid the foundation for understanding biological changes in facial features over time and emphasized age-specific shape modeling.

Antipov, Baccouche, and Duge lay [2] developed *"Face Aging with Conditional Generative Adversarial Networks"*, a class-conditional GAN model that allowed precise age-group transformation. By leveraging age labels as input, their method preserved facial identity better than prior morphing techniques and improved visual output stability.

Zhang, Song, and Qi [3] proposed *"Age Progression/Regression by Conditional Adversarial Autoencoder"*, which enabled both aging and de-aging while preserving identity using a latent space that disentangled age and facial features. Their method achieved consistency across varying age representations and supported reversible transformations.

Seo, Park, and Kim [4] introduced *"Age Transformer: Self-Attention Based Face Aging Synthesis"*, where Transformer-based attention captured long-range dependencies in facial features. Their work improved global consistency and enabled detailed yet structured aging transformations beyond local receptive fields of CNNs.

Li, Liu, and Wang [5] presented *"Global and Local Consistent Age Generative Adversarial Network (GLCA-GAN)"*, a model combining holistic and region-specific facial aging. It modelled both global structural deformations and local aging effects like wrinkles, achieving superior photorealism and texture fidelity.

Chen, Yang, and Wang [6] developed *"Attention-Driven Face Aging GAN"*, which employed channel and spatial attention to emphasize age-sensitive regions such as the forehead and eyes. Their approach provided better focus on wrinkle formation and skin tone variation, enhancing the realism of synthesized aging effects.

Huang, Wei, and Zhang [7] proposed *"Memory-Augmented Face Aging with GANs"*, integrating a memory network to capture long-term age progression trends across diverse individuals. This memory component allowed the model to leverage aging knowledge from previously seen samples to generate more realistic and continuous face aging results.

Xu, He, and Feng [8] proposed *"Progressive Aging GAN with Identity Consistency Loss"*, introducing an identity-aware training objective to ensure accurate identity preservation across age progression. The model generated sequential aging stages with stable facial features, maintaining a natural age progression curve.

## ARCHITECTURE:

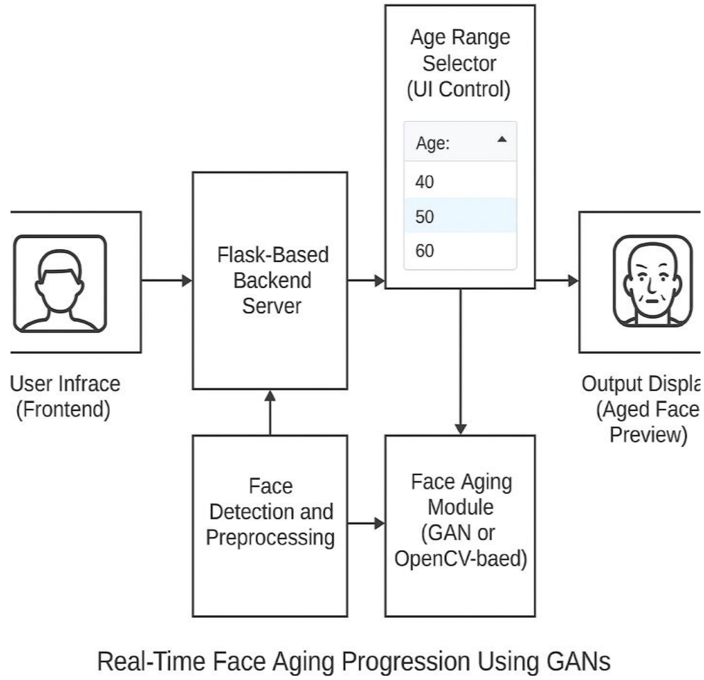


Fig 1: System Architecture

## EXISTING SYSTEM:

The existing system for face aging progression primarily utilizes traditional image processing techniques, such as facial morphing, histogram equalization, and wrinkle simulation through OpenCV-based filters. These methods typically rely on predefined patterns or handcrafted overlays to mimic age-related changes, including skin dullness, wrinkle enhancement, eye bag darkening, and greying of hair. While these simulations can be applied in real-time due to their low computational cost, they are limited in generating personalized or data-driven outputs. These conventional techniques lack the ability to learn from large-scale age-progressed datasets, leading to generic transformations that do not accurately reflect the natural aging process. They fail to model the biological factors associated with aging, such as muscle weakening, bone structure changes, and texture redistribution. Furthermore, identity preservation is not maintained effectively, often resulting in outputs where facial features get varies.

## PROPOSED SYSTEM:

The proposed system leverages deep learning and GAN-based techniques to generate realistic, identity-preserving facial aging transformations in real time. It is built around a Flask-based web application that allows users to upload or capture their facial image and select an age group (e.g., 20–35, 40–55, 60–70, 70+). Once an image is received, the system uses OpenCV to detect and preprocess the face by aligning, cropping, and normalizing it to match the input requirements of the aging model. Th core face aging module is powered by either pretrained GAN models (such as PFA-GAN or CAAE) or custom-trained GANs capable of generating photorealistic aged faces conditioned on the selected age group. These models effectively simulate aging features—such as wrinkles, sagging skin, and pigmentation—while preserving unique identity traits like facial structure and expression. The Flask backend routes the input through the selected age model and returns the aged output, which is then displayed on the web interface for visualization. The system ensures natural age progression, smooth transitions between age groups, and supports extensibility for further integration of attributes like gender or ethnicity adaptation in future enhancements.

## METHODOLOGY

The methodology for real-time face aging progression using Generative Adversarial Networks (GANs) involves a systematic approach, covering data collection, model selection, training, optimization, and real-time deployment. The methodology consists of the following key phases:

1. **Data Collection and Preprocessing:** A high-quality and diverse dataset is essential for training the face aging model. The dataset should contain facial images of individuals across different age groups, ensuring a balanced representation of age, gender, ethnicity, and facial variations. Dataset Selection, Data Cleaning and Augmentation, Facial Alignment and Normalization are parts of it.

2. **Model Selection and Architecture Design:** GAN-based architectures have been widely used for face aging progression due to their ability to generate high-resolution and identity-preserving transformations. Various GAN models can be considered Conditional GANs (c GANs), StyleGAN, Star GAN etc.

3. **Model Training and Optimization:** The training phase involves feeding facial images of different age groups into the GAN model to learn aging transformations.

4. **Real-Time Processing and Performance Optimization:** To achieve real-time performance, several optimizations are implemented, Such as Model Pruning and Compression, Quantization, GPU Acceleration and Parallel Processing.

5. **User Interface and System Deployment:** Once the model is trained and optimized, it is integrated into a user-friendly application for real-time face aging progression.

   **Frontend Development:** A web or mobile-based interface is developed using React.js, Flask, or Node.js for user interaction.

   **Backend and API Integration:** The trained GAN model is deployed as a REST API using Flask, Fast API, or TensorFlow Serving.

6. **Evaluation and Testing:** The system is evaluated using multiple metrics to ensure high accuracy, realism, and efficiency.

**RESULTS & ANALYSIS:**

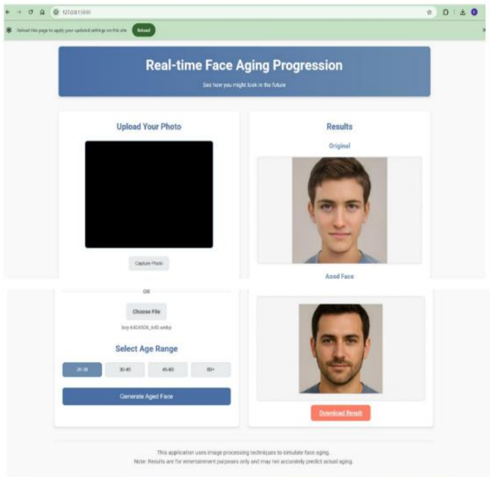


Fig 2: Aging between the age range 20-30

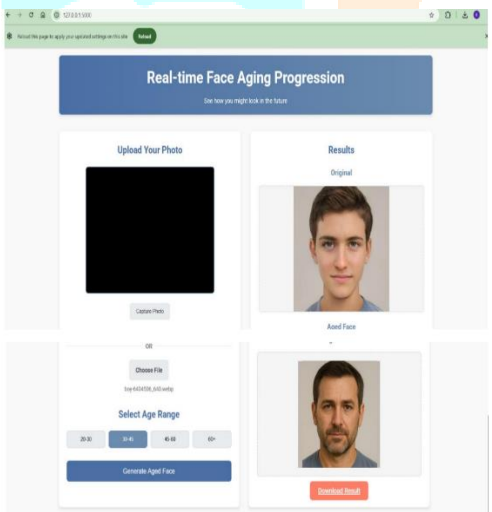


Fig 3: Aging between the age range 30-45

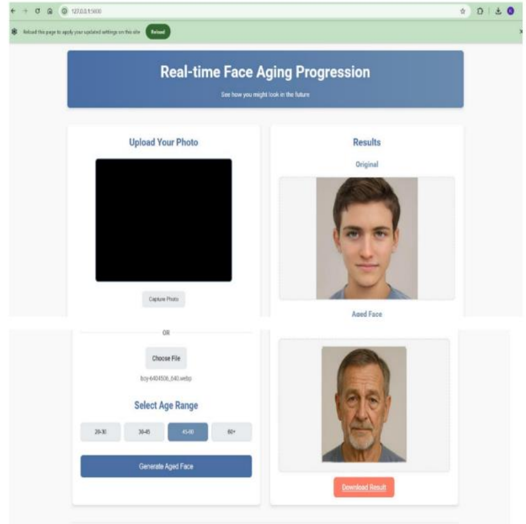


Fig 4: Aging between the age range 45-60

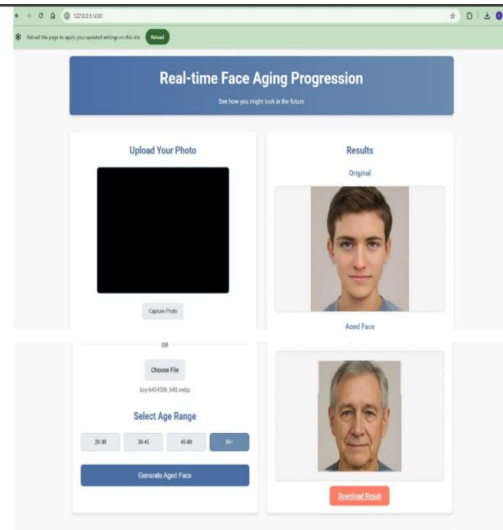


Fig 5: Aging After 60+

**CONCLUSION:**

This project successfully implements a real-time face aging progression system using a Flask-based web application integrated with OpenCV. The application allows users to upload or capture facial images and simulate aging effects based on selected age groups (20–30, 30–45, 45–60, 60+). The system leverages pre-defined OpenCV image processing techniques to simulate wrinkles, grayscale transformation, facial sagging, and other visual cues associated with aging. The lightweight nature of the implementation ensures fast and responsive performance in real-time, making it suitable for deployment on edge devices and low-resource environments. While the current system does not use a deep learning model like PFA-GAN for the actual aging effect, it lays a solid foundation for future integration of GAN-based transformations, combining real-time performance with photorealistic accuracy. This work demonstrates the feasibility of interactive aging simulation with minimal computational overhead and offers a usercentric platform for practical applications in entertainment, digital forensics, and aging research works.

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