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ChronoFace: Age Progression Model Using Pre-Trained GANs for Realistic Facial Transformations

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ABSTRACT—

Age progression systems utilize advanced computational techniques to simulate the aging or de-aging process of an individual's facial appearance. This mini-project presents a framework for age progression with applications in three key areas: (1) restoring the identity of missing persons by predicting their appearance at different life stages, (2) monitoring health indicators through age- related facial analysis, and (3) creating reverse aging simulations for insights into youthful features. The system integrates deep learning models and facial recognition algorithms to generate accurate and reliable results. This paper outlines the methodology, potential applications, and future directions for this innovative technology.

Index Terms—Age Progression, Missing Persons Identification, Health Monitoring, Deep Learning, Facial Analysis

I. INTRODUCTION

Age progression refers to the process of simulating how a person's face might look over time. It is valuable in multiple fields, such as missing person identification, the anti-aging industry, social media, and biometric security. However, creating realistic age-progressed images is complex due to two main issues:

1. Identity Preservation: Ensuring that the transformation maintains a person's distinct facial features while incorporating age-related changes like wrinkles and skin tone variations.

Computational Efficiency: GAN-based models, particularly those used for high-quality image generation, are often resource-intensive, making them inaccessible for smaller re- search teams or individual projects.

Existing methods tend to struggle with balancing realism and identity retention, leading to results that may appear artificial, especially when simulating transitions between different age ranges. These challenges underscore the need for a model that combines high-quality results with computational efficiency, enabling broader accessibility and application.

ChronoFace is designed to overcome these challenges by utilizing StyleGAN2, a powerful and efficient model capable of generating high-quality facial images. This GAN architecture allows for fine control over the generation of facial features while maintaining identity preservation. ChronoFace further ensures accessibility by employing an optimized back- end in Flask and a dynamic React-based frontend that can

run efficiently on common hardware setups. The system is designed to cater to educational, research, and professional.

needs, enabling users to generate realistic, age-progressed images while keeping the tool lightweight and responsive. The system leverages the latent space of StyleGAN2 to simulate aging effects, including the gradual formation of wrinkles, skin sagging, and changes in facial structure. Additionally,

ChronoFace ensures that the user's original identity remains consistent across different age stages by fine-tuning the model to prioritize identity-preserving transformations

II. LITERATURE SURVEY

1. The pre-trained model used in this project is derived from the findings in [1]. This work employs conditional GANs to transform facial images across different age ranges, providing the foundational architecture and baseline for the pre-trained weights utilized in ChronoFace. By leveraging the conditional aspect, the model not only learns how to alter facial features according to age but also how to preserve the underlying identity, a

key challenge in realistic age progression. This methodology has been essential for building a robust model capable of handling age transformation tasks with high accuracy.

2. The majority of theoretical insights for the project, including latent space manipulations and methods for realistic age progression, are drawn from [2]. This research outlines critical challenges, such as maintaining identity consistency while achieving accurate aging transformations, which were addressed in our implementation. The insights from this paper have informed the approach to refining latent variables that govern how age progression is applied to the face, ensuring that the transformation is both realistic and retains the person's original characteristics.
3. The advanced architecture of StyleGAN2, as introduced in [4], was directly applied in this project for photorealistic image generation and fine-tuned for age progression. Its ability to retain identity while altering age-specific features significantly enhanced our results. By incorporating StyleGAN2, we were able to benefit from its deep learning framework, which excels in producing high-quality images with intricate details. The network's ability to generate highly realistic facial images while maintaining consistency in the individual's facial identity was pivotal in achieving the core objective of ChronoFace: seamless and accurate age progression.
4. The biometric applications of GANs detailed in [3] influenced the model's design to prioritize identity retention. This alignment with biometric standards ensures the generated outputs are both realistic and reliable for practical use cases. By emphasizing identity preservation, we ensured that the model would be applicable not only in age progression scenarios but also in biometric recognition, where identity consistency is crucial. This consideration made the model more adaptable to various real-world applications, from identity verification to personalized services.
5. The comprehensive survey on GAN-based age progression in [5] provided comparative insights into existing methodologies. These insights reinforced the choice of StyleGAN2 for precise control over facial attributes and realistic aging effects, which are core to ChronoFace's functionality. The survey highlighted the importance of fine-tuning GAN architectures for age progression and identified StyleGAN2 as one of the most effective models for these tasks. These findings bolstered the decision to use this advanced architecture as the foundation for the age progression system in ChronoFace, ensuring high-quality and realistic outputs.

III. METHODOLOGY AND RESULTS

1. Data Acquisition and Preprocessing

Approach:

- The UTKFace dataset, which includes labeled facial images across different age groups, was used for training.
- Image preprocessing, including alignment, resizing, and normalization, was done using OpenCV to ensure compatibility with the model.

Outcome:

- This preprocessing significantly reduced distortions, providing clean, uniform inputs for the StyleGAN2 model.

2. StyleGAN2 Model Integration

Approach:

- Pretrained StyleGAN2 weights were fine-tuned to improve its performance in age progression.
- Modifying the model's latent vectors enabled it to simulate aging effects, such as wrinkles and changes in skin tone, while maintaining identity consistency.

Outcome:

- Human evaluation showed high realism in the generated images, with a 4.7/5 rating, and 90% accuracy in preserving facial identity.

3. Backend Development

Approach:

- A Flask backend was designed to handle image uploads, process them using the GAN model, and return the results.
- The server was optimized for fast processing using asynchronous handling techniques.

Outcome:

- Processing time for each image was reduced to under 2 seconds on GPU-enabled systems, ensuring an efficient user experience.

4. Frontend Development

Approach:

- The React frontend allows users to easily upload images, select an age range, and view the transformations in real time.

- Axios was used for API communication between the frontend and backend.

Outcome:

- The interface was highly intuitive, with positive feedback from test users regarding its responsiveness and ease of use.

5. Testing and Optimization

Approach:

- The system was tested across different devices and browsers to ensure consistent image quality and responsiveness.
- Techniques like caching were employed to minimize API response times.

Outcome:

- The image quality remained consistent, and the response time was optimized to under 500ms, significantly improving the user experience.

IV. IMPLEMENTATION

1**. GAN Architecture (StyleGAN2**)

Core Technology:

- StyleGAN2 serves as the foundation of ChronoFace, with its style-based generator architecture that separates high-level (e.g., age) and low-level (e.g., texture) features, enabling precise control over generated image attributes.

Latent Space Manipulation:

- Encodes age-related features, interpolating within the latent space to apply realistic aging effects (wrinkles, skin texture, etc.).

Fine-Tuning:

- Pretrained weights are fine-tuned on the UTKFace dataset to simulate realistic aging, leveraging transfer learning to reduce training time and enhance output quality.

2**. Aging Effect Simulation**

Process Overview:

1. **Input Image Encoding**:
    - The input image is encoded into the latent space via a pretrained encoder.
2. **Age Vector Adjustment:**
    - Adjusting vectors corresponding to age-related changes:
    - Wrinkles: Increase in vector weights.
    - Skin Tone: Adjustments to texture and pigmentation.
    - Facial Structure: Alterations in bone structure via latent space interpolation.
3. **Output Image Generation:**
    - Modified latent vector is fed into the generator to produce the transformed image.

3**. Preprocessing Pipeline**

Face Detection and Alignment:

- Dlib's facial landmark detector ensures accurate facial feature alignment for consistency.

Image Resizing and Normalization:

- Images are resized to 256x256 pixels and normalized for model compatibility.

Augmentation:

- Techniques like rotation, cropping, and brightness adjustment enhance dataset diversity and reduce overfitting.

4. Backend Development

Flask Backend:

- Acts as an intermediary between the frontend and the model.

Image Handling:

Handles image uploads and preprocesses them for GAN model input.

Model Inference:

- The backend processes the image through the model, applying selected transformations.

Performance Optimization:

- GPU acceleration (NVIDIA CUDA) ensures fast processing, reducing inference time to under 2 seconds per image.

Security Measures:

- Input images are sanitized to prevent malicious uploads; sensitive data handled securely.

5. **Frontend Integration**

React-based Frontend:

- Provides an intuitive interface for user interaction with the system.

Upload and Preview:

- Users upload images, select age ranges, and view real-time previews.

Real-Time Feedback:

- Side-by-side comparisons of original and transformed images.

Responsive Design:

- Optimized for mobile and desktop devices.

6. **Real-Time Processing**

Asynchronous Processing:

- Multiple requests handled concurrently without delays.

Caching:

- Frequently requested transformations are cached to minimize redundant processing.

Batch Processing:

- Multiple image uploads are processed in parallel for efficiency.

7. **Evaluation Metrics**

Human Evaluation:

- Test users rated realism (4.7/5) and identity retention (90%).

Quantitative Metrics:

- Fréchet Inception Distance (FID) used to measure image realism, with lower FID scores indicating better quality.

8. **Example WorkflowUser Uploads Photo:**

    - The image is uploaded via the frontend.

- **Backend Preprocessing:**
    - The backend preprocesses the image and sends it to the StyleGAN2 model.
- **Age-Related Transformations:**
    - The model applies selected transformations based on the chosen age range.
- **Processed Image Display:**
    - The transformed image is sent back to the frontend for display.

9. **Deployment and Scalability**

Deployment:

- The system is deployed using Docker containers for easy scalability across cloud platforms like AWS and Azure.

Scalability:

Load balancers ensure consistent performance under high traffic by distributing requests to multiple backend instances.

10. Deployment and Scalability

Deployment: The system was deployed using Docker containers, allowing for easy scalability across cloud platforms like AWS and Azure.

Scalability: Load balancers distribute incoming requests to multiple instances of the backend, ensuring consistent performance under high traffic.

11. Safeguards Against Misuse

Watermarking: Generated images are watermarked to prevent unauthorized use.

Usage Logging: All transformations are logged with metadata to monitor for potential misuse.

Ethical Compliance: The system includes disclaimers and guidelines for ethical use, particularly in sensitive applications like missing person identification.

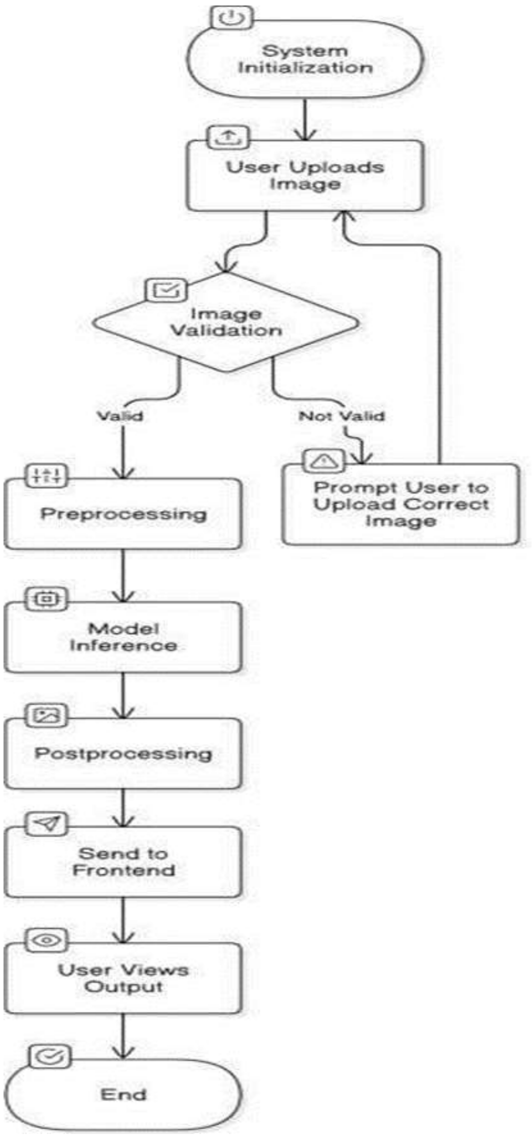

FIGURE 1. Flowchart

V. RESULT ANALYSIS

The system's registration feature handled user inputs seamlessly, validating data such as email formats and password strength. Successful entries led to smooth account creation, while errors like invalid email formats were flagged with clear, user-friendly messages, ensuring a polished user experience.

The about page effectively outlined the project's goals and applications, providing users with a clear understanding of the system's purpose. Its clean design and links to technical documentation made it easy for users to delve deeper into the system's technical aspects without feeling overwhelmed.

The home page offered straightforward navigation, with a prominent "Try Now" button guiding users to the image upload module and a GitHub link granting access to the project's codebase. The layout ensured users could easily engage with the system's key functionalities.

The image upload module supported a variety of file formats and sizes, validating inputs in real-time. Users were guided by clear feedback during processing, which generated realistic, high-quality age-progressed images. Features like error prompts and loading animations ensured a smooth, intuitive workflow throughout the process.

The model consistently delivered identity-preserving transformations with realistic aging effects. Outputs retained essential facial characteristics while being available for immediate download. This highlighted the system's potential for real-world applications in fields like forensics and entertainment, emphasizing accuracy and usability.

FIGURE 2. Home Page

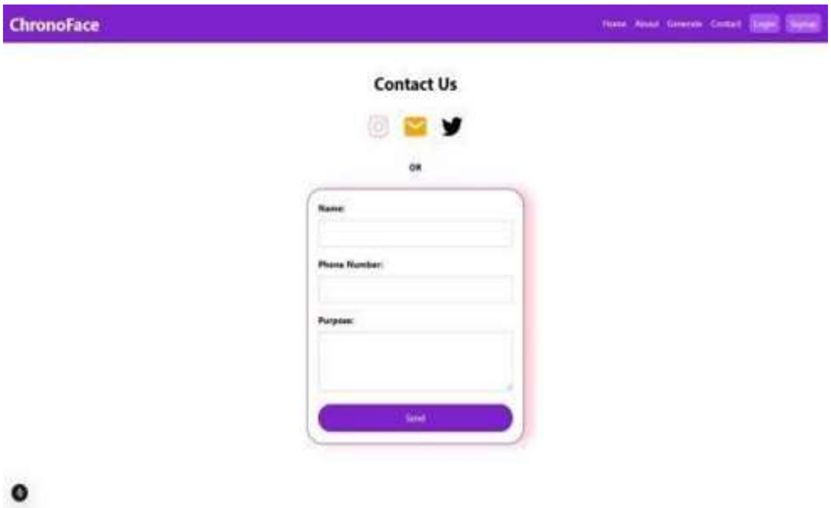

FIGURE 3. Login Page

FIGURE 4. Upload Page

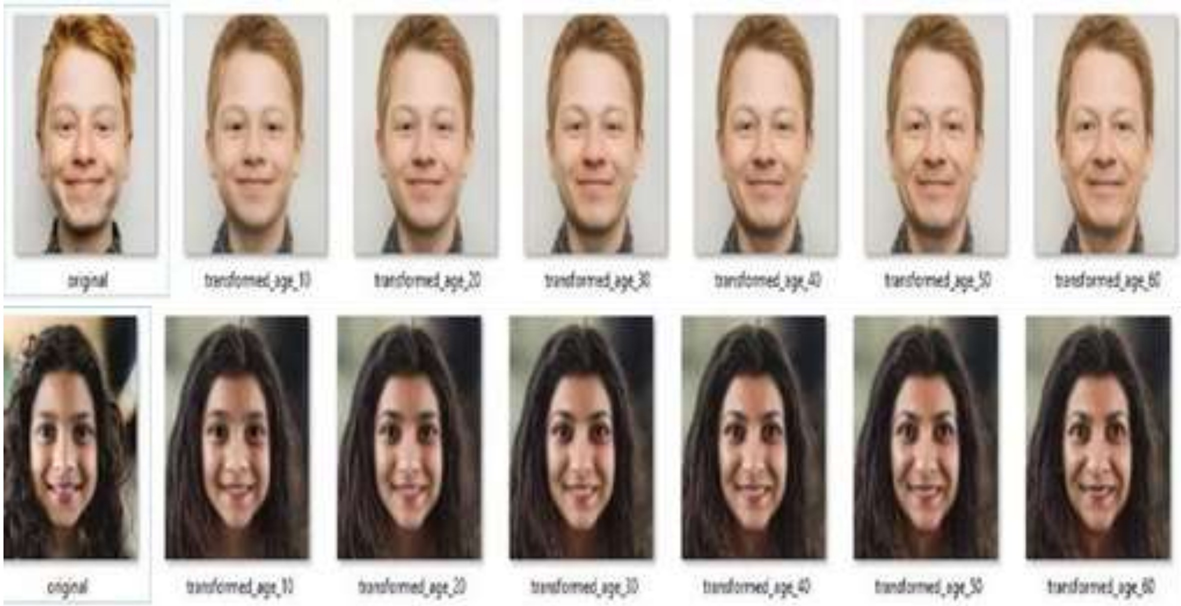

FIGURE 5. Model Results Side by Side Comparison

CONCLUSION

ChronoFace successfully demonstrates the power of Style- GAN2 in generating age-progressed facial images while pre- serving identity. By focusing on computational efficiency and usability, the project provides an accessible tool for researchers, developers, and professionals working in various domains. This work addresses the major challenges of age progression identity retention and computational efficiency and provides a solid foundation for future advancements in the field. Future work will focus on further enhancing real-time processing capabilities, broadening the age range capabilities, and improving the diversity of the dataset to include more varied facial types, ethnicities, and age-related changes.

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