

Facial Age Estimation from Image Using Image Processing Techniques and Neural Network

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Abstract : It has been recently shown that Generative Adversarial Networks (GANs) can produce synthetic images of exceptional visual fidelity. In this work, we propose the first GANbased method for automatic face aging. Contrary to previous works employing GANs for altering of facial attributes, we make a particular emphasize on preserving the original person's identity in the aged version of his/her face. To this end, we introduce a novel approach for "Identity Preserving" optimization of GAN's latent vectors. The objective evaluation of the resulting aged and rejuvenated face images by the state-of-the-art face recognition and age estimation solutions demonstrates the high potential of the proposed method

Keywords : Facial Age Estimation, Image Processing, Neural Networks, Computer Vision, Age Prediction, Feature Extraction, Pattern Recognition

I. INTRODUCTION

Face aging, also known as age synthesis and age progression, is defined as aesthetically rendering a face image with natural aging and rejuvenating effects on the individual face. It has plenty of applications in various domains including cross-age face recognition, finding lost children and entertainment. Traditional face aging approaches can be roughly split between the prototyping ones and the modeling one. Prototyping approaches estimate average faces within predefined age groups. The differences between these faces constitute the aging patterns which are further used to transform an input face image into the target age group.

II. Literature SURVEY

Thomas S Huang (2010) Human age, as an important personal trait, can be directly inferred by distinct patterns emerging from the facial because of their explosively emerging real-world applications, such as forensic art, electronic customer relationship management, security control and surveillance monitoring, biometrics, entertainment, and cosmetology. Age synthesis is defined to render a face image aesthetically with natural aging and rejuvenating effects on the individual face.

M. Mindyarto and M. J. Gierl (2023) This research presents a systematic approach to evaluating the quality, usability, and validity of automatically generated test items. The study compares AIG-generated items with manually written questions in a large-scale assessment context. Using psychometric evaluation techniques, the authors assess item difficulty, discrimination index, and response time. The results reveal that while AIG can produce questions comparable to human-written ones, some items show inconsistencies due to variations in linguistic complexity and cognitive load.

Hanjiang Lai, Luoqi Liu, and Shuicheng Yan (2015) In this paper, we aim to automatically render aging faces in a personalized way. Basically, a set of age-group specific dictionaries are learned, where the dictionary bases

corresponding to the same index yet from different dictionaries form a particular aging process pattern cross different age groups, and a linear combination of these patterns expresses a particular personalized aging process.

X. W. Chen and X. Lin.(2010) Age-invariant face recognition is one of the most crucial computer vision problems, e.g., in passport verification, surveillance systems, and missing individuals identification. The extraction of robust face features is a challenge since the facial characteristics change over age progression. In this paper, an age-invariant face recognition system is proposed, which includes four stages: preprocessing, feature extraction, feature fusion, and classification. Preprocessing stage detects faces using Viola–Jones algorithm and frontal face alignment.

III. Methodology

It can be seen in Figure that the optimized reconstructions are closer to the original images than the initial ones. However, the choice is more complicated when it comes to the comparison of the two latent vector optimization approaches.

A. Dataset

Age-cGAN has been trained on the IMDB-Wiki cleaned dataset of about 120K images which is a subset of the public IMDB-Wiki dataset. More precisely, 110K images have been used for training of Age-cGAN and the remaining 10K have been used for the evaluation of identity preserving face reconstruction..

B. Age-Conditioned Face Generation

Figure illustrates synthetic faces of different ages generated with our Age-cGAN. Each row corresponds to a random latent vector z and six columns correspond to six age conditions y . Age cGAN perfectly disentangles image information encoded by latent vectors z and by conditions y making them independent. More precisely, we observe that latent vectors z encodes person's identity, facial pose, hair style, etc., while y encodes uniquely the age.

C. Identity-Preserving Face Reconstruction and Aging

We perform face reconstruction (i.e. the first step of our face aging method) in two iterations: firstly, (1) using initial latent approximations obtained from the encoder E and then (2) using optimized latent approximations obtained by either “Pixel wise” or “Identity Preserving” optimization approaches. Some examples of original test images, their initial and optimized reconstructions are presented.

D. Prediction

It can be seen in Figure that the optimized reconstructions are closer to the original images than the initial ones. However, the choice is more complicated when it comes to the comparison of the two latent vector optimization approaches. On the one hand, “Pixelwise” optimization better reflects superficial face details: such as the hair colour in the first line and the beard in the last line. On the other hand, the identity traits (like the form of the head in the second line or the form of the eyes in the first and last lines) are better represented by “Identity-Preserving” optimization.

IV. SYSTEM ARCHITECTURE

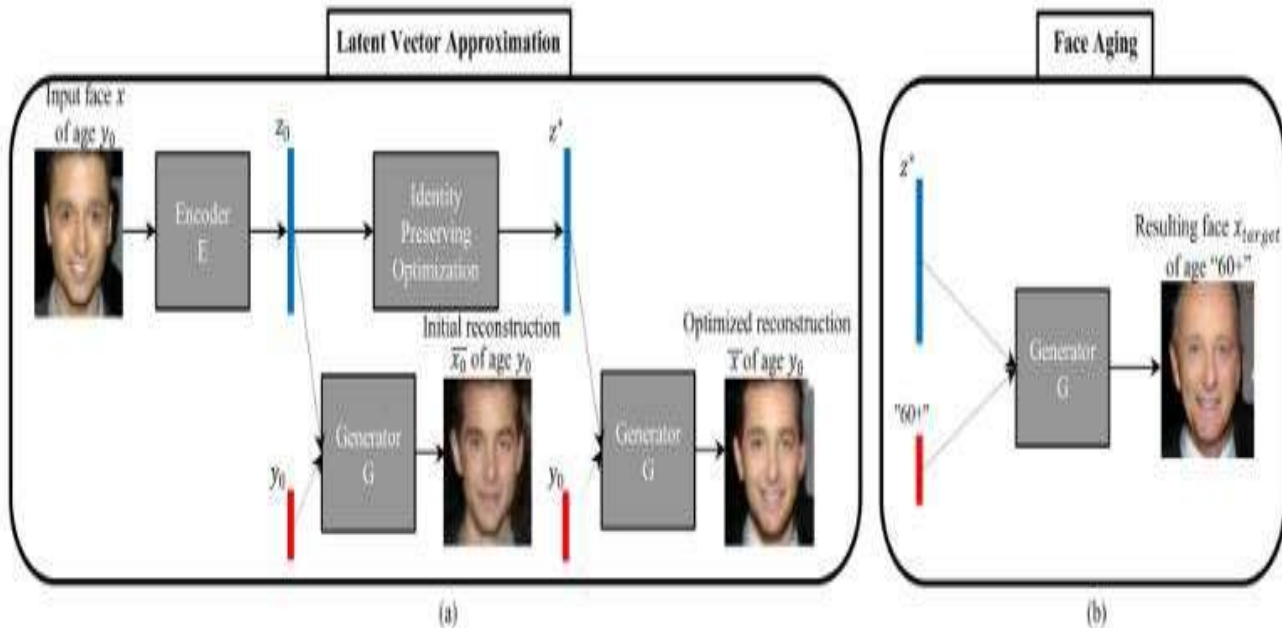


Fig 1: System Architecture

V. IMPLEMENTATION

The proposed project is implemented as a synthetic face aging and rejuvenation system using a Generative Adversarial Network (GAN) architecture, specifically an Age-Conditional Generative Adversarial Network (Age-cGAN). The main aim is to automatically age a face while emphasizing the preservation of the original person's identity, which is a significant advancement over previous works that simply alter facial attributes. The system consists of distinct functional models: an Encoder, a Generator, and an Identity-Preserving Optimization module. These components interact to disentangle the image information into a latent vector encoding the person's identity and a condition vector encoding the target age

secure authentication and automatic vote counting is involved in the process to ensure the reliability of the election process.

The architecture splits the system into various modules, including user management, authentication, voting process, and results. This division ensures that the software is scalable, modular, and highly performant. Blockchain technology is used for storing all transactions done during voting to prevent any manipulation and unauthorized access. Smart contracts are deployed for automating critical operations like vote verification and calculation of voting results.

AGE-CONDITIONED FACE GENERATION

Once the optimized latent vector is secured, the actual face aging simulation is performed. The Age-cGAN perfectly disentangles the image information. The optimized latent vector encodes the identity, facial pose, and hair style, while a separate condition vector uniquely encodes the target age. The target age condition is modified (e.g., set to "60+") and combined with the optimized latent vector at the input of the Generator to render the final synthetically aged or rejuvenated face.

SYSTEM TESTING AND EVALUATION

To evaluate the effectiveness of the implementation, a comprehensive software testing framework is established. The system undergoes various testing methodologies, including Unit testing (to validate internal program logic), Functional testing (to ensure valid and invalid inputs are handled correctly), System testing (to ensure predictable integrated results), and Performance testing (to ensure responses are within acceptable time limits). The objective evaluation compares the initial reconstructions against the optimized reconstructions to prove that the optimized outputs are closer to the original images.

VISUALIZATION AND REPORTING

The final step is to present the results generated by the Age-cGAN. The outputs are visualized using structural grids that showcase the original test images alongside their initial and optimized reconstructions (comparing Pixelwise vs. Identity-Preserving results). Furthermore, the system outputs the final age progression by displaying synthetic faces of the same identity mapped across six distinct age condition columns (0-18, 19-29, 30-39, 40-49, 50-59, and 60+)

VI. RESULTS

URL

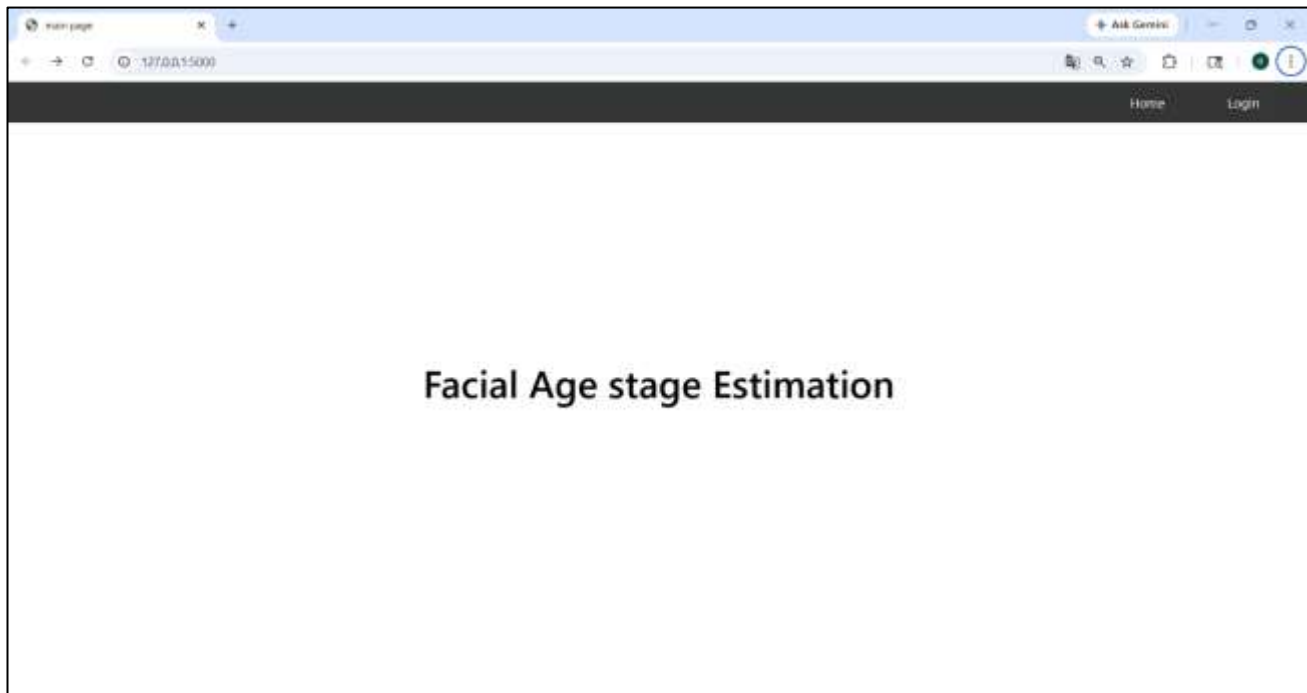


Fig 1: Url

when we run the code in Anaconda we will get project URL, by pasting it any kind of search engine we get the output.

LOGIN PAGE

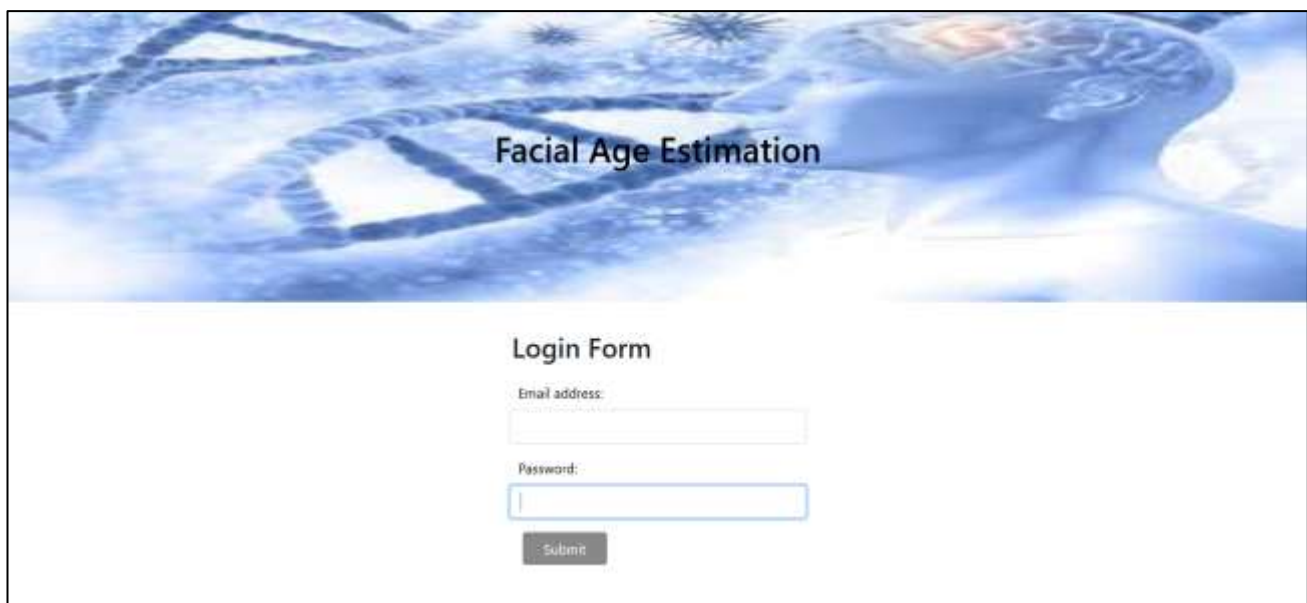


Fig 2: Login page

This is User Login Interface of the application Users would input their credentials like username and password and proceed to the main functionalities of the "Model-Based Learning for Mapping Locations to Optimal Communication Channel" project.

INPUT PAGE

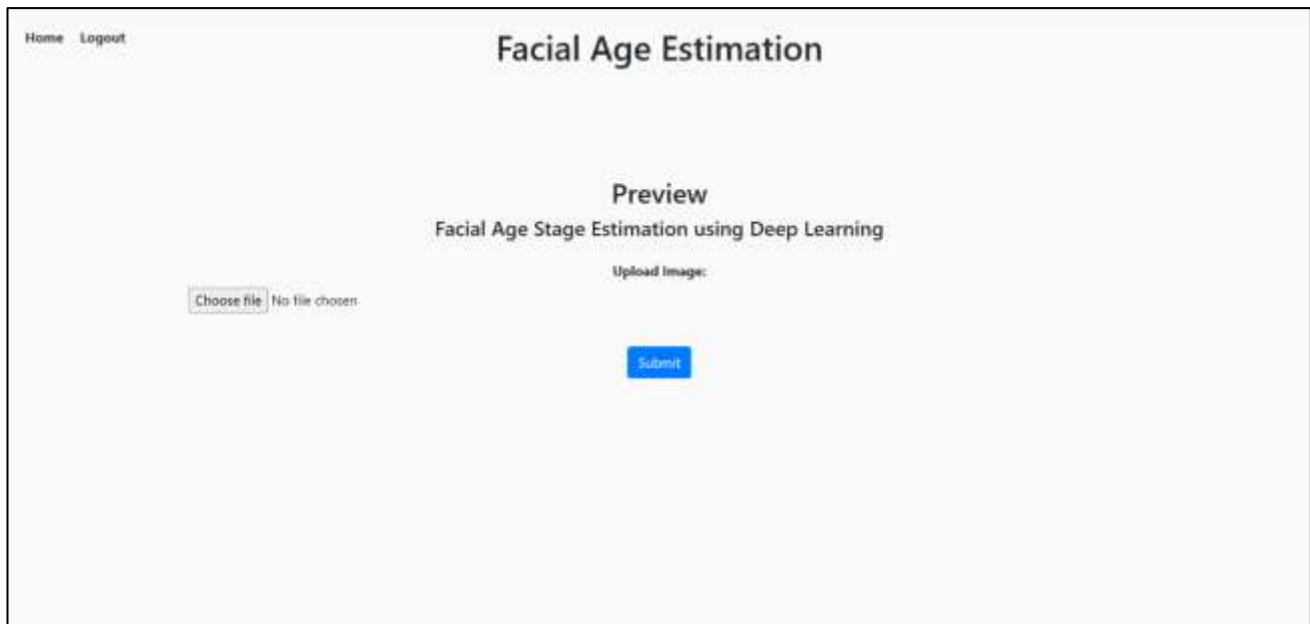


Fig 3 : Input page

This screen is the Face age estimation Prediction Input Interface. It allows users to enter key network parameters (signal strength, throughput, latency, and specific hardware/software radio measurements like dBs , ms) etc for the model to predict the optimal communication channel.

OUTPUT PAGE

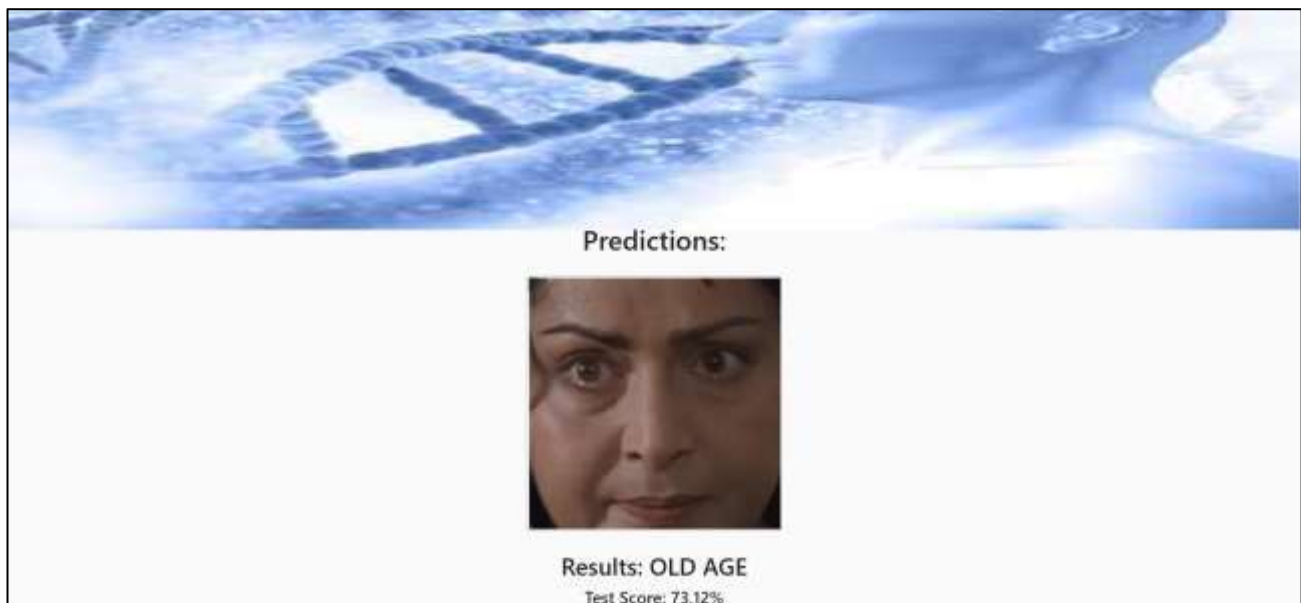


Fig 4: Output page

This output screen shows the Network Type Prediction Result, where the model has processed the input parameters and determined that 'Network Type 2' i.e 2G is the optimal communication channel.

VII. CONCLUSION

In this work, we have proposed a new effective method for synthetic aging of human faces based on Age Conditional Generative Adversarial Network (Age-cGAN). The method is composed of two steps: (1) input face reconstruction requiring the solution of an optimization problem in order to find an optimal latent approximation z^* , (2) and face aging

it-self performed by a simple change of condition y at the input of the generator. The cornerstone of our method is the novel “Identity Preserving” latent vector optimization approach allowing to preserve the original person’s identity in the reconstruction. This approach is universal meaning that it can be used to preserve identity not only for face aging but also for other face alterations (e.g. adding a beard, sunglasses etc.)

VIII. FUTURE ENHANCEMENT

It is part of our future work. Moreover, we believe that the face reconstruction part of our method can be further improved by combining “Pixelwise” and “Identity-Preserving” approaches into one optimization objective. We are also planning to explore this path in our further studies.

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