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A NOVEL APPROACH FOR FACIAL AGING BASED ON CYCLEGAN

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Abstract: Face aging is a fascinating and challenging task in the field of computer vision, with applications in entertainment, cosmetics, and forensics. In recent years, the CycleGAN framework has emerged as a powerful approach for face aging, enabling the transformation of facial images between different age groups without the need for paired training data. This abstract presents a unique exploration of face aging using CycleGAN, focusing on the generation of realistic and visually convincing aged faces from young faces. By leveraging the principles of generative adversarial networks (GAN) and cycle consistency, the proposed method captures and transfers the intricate facial details associated with aging, including wrinkles, fine lines, and skin texture changes. The training process involves optimizing the discriminator and generator components, with the training losses serving as crucial indicators of the model's convergence and learning progress. Through experiments and evaluations, the effectiveness and potential applications of the proposed approach are demonstrated, highlighting its contributions to the field of facial aging and its implications for various industries.

Keywords: Face Aging, Generative Adversarial Networks, CycleGAN, Artificial Face, Deep Learning

Introduction

An interesting field of research that studies revolves around face ageing, which uses cutting-edge computational techniques and artificial intelligence methods to produce artificially real simulations regarding the way somebody's face may change over a period of time. Intelligent deep learning approaches are taught to understand the intricate features and transform related to ageing by analyzing massive datasets of face photos and capturing essential facial traits, such as signs of ageing, complexion, and hair colour [1]. When applied to input photographs of youthful or middle-aged faces, the suggested models may then be utilised to create older copies of those faces, replicating the impact of ageing with a surprising level of precision and complexity. In the forensic field, age-progressed images of missing people are produced, and in cosmetics manufacturing, artificial face ageing is used to visualize the possible consequences of cosmetics and medications. Artificial face ageing has many uses in both the entertainment and fields of forensic science. Several crucial phases are involved in the artificial face ageing procedure. An extensive dataset of facial photographs from various demographics and age groups is first gathered [2]-[3]. Then, using cutting-edge artificial intelligence techniques, face characteristics and behaviours are extracted from the dataset to capture the small modifications that take place with ageing. Then, based on this information, deep learning techniques, specifically deep systems, are developed to predict the ageing procedure and discover the complex correlations between face characteristics and age development.

The learnt ageing processes and numerous face features may be applied to input photographs to change images when the performers have been built and evaluated. To improve the accuracy of the findings and the entire authenticity of the artificial ageing impact, further post-processing procedures may be used. The area of artificial face ageing is being driven by ongoing developments in deep learning and computational recognition techniques, which allow for more precise and aesthetically arresting simulation of facial ageing [4].

The inspiration for artificial facial ageing comes from an innate interest and interest over time and how it affects how we look. People have long been interested in the idea of ageing and potential upcoming appearances. Through exploration and visualization of these changes, artificial face ageing offers a window into the possible impacts of ageing on our faces. This technology provides beneficial applications in many different domains in addition to satisfying everything innate interest. For instance, it allows developers in the entertainment sector to portray individuals at various phases of everything in order with astounding precision [5]-[6]. Artificial face ageing is used in forensics to create age-progressed photographs of missing people, which may aid in their identification after substantial gaps in time. In addition, through modelling the impacts of long-term ageing and aiding in the comprehension of age-related illnesses, artificial face ageing can support scientific study. The problem of synthetic face ageing encompasses several challenges and considerations that researchers and practitioners in the field must address. One significant issue is the accurate representation of facial ageing. Capturing the complex and nuanced changes that occur in a person's face over time is a difficult task. Facial ageing involves a combination of various factors, including skin texture, wrinkles, facial volume loss, and changes in hair colour, all of which need to be realistically simulated in synthetic face ageing [7]-[8]. Ensuring that the generated aged faces are visually convincing and align with the expectations of human observers requires sophisticated algorithms and models that can capture the intricacies of the ageing process.

The main contribution of the paper

The study on face aging using CycleGAN with unique contents makes several significant contributions to the field. Firstly, it presents a novel approach for face aging that utilizes the power of CycleGAN to generate realistic and visually appealing aged faces from young faces.

By eliminating the need for paired training data, the method offers more flexibility and scalability in generating age transformations. Secondly, the study explores and captures intricate facial details associated with aging, such as wrinkles, fine lines, and skin texture changes, ensuring the generated aged faces exhibit high fidelity and naturalness. Additionally, by analyzing the training losses of the discriminator and generator, the study provides insights into the convergence and learning dynamics of the model, aiding in model optimization and enhancing the quality of generated aged faces. Overall, this research expands the understanding and capabilities of face aging techniques, opening doors to various applications in industries such as entertainment, cosmetics, and forensics.

Related Work

This section is preceded by earlier research in the ageing face detection field. Investigators are currently focusing their research on the problems of facial recognition, detection, and validation. The two main categories of this study are locally and globally methods. Face models are generated as generative models via global techniques. Global Strategies must create fabricated photographs of the subject at the necessary aged and then compare them to the original image. Facial models are produced locally as discriminatory algorithms.

For two images of an identical person to be comparable, regional methods require a unique method of feature extraction and categorization. In addition to the procedures mentioned earlier, models of conventional techniques are created manually. Deep neural networks are currently attracting a lot of interest.

Global Perspectives

For global techniques, one face picture is often changed from a single age to the appropriate age, which is referred to as the age simulator approach, to lessen the ageing impact. For the purpose of addressing the issue of ageing identification of faces, a two-level training hierarchies' model-based method is previously given in [9] using a feature descriptor termed LPS.

The SVM and Active Appearing Simulations, and a Monte-Carlo based face ageing model with great modelling effectiveness were proposed by Sethuram et al. [10].

For individuals under the young age of 20 Ramanathan and Chellappa [11] suggested a face-growing approach for the identification of faces as people become older.

In a framework for the developing face that Lanitis et al. [12] provided, the learning set has been calculated on the modeling environment for face detection. The resulting face model, a blend of shape and luminance models, had 50 model variables. After the age estimate using an appropriate ageing operation, the modelling variables are then changed to updated sets of attributes to be compatible with the desired age.

A general approach that uses a 3D ageing model to enhance identifying faces performance was put out by Park et al. [13]. For form and texture, their employed different modelling steps and position modifications.

Local Perspectives

For local approaches, facial photos of people gathered at various ages are subjected to strong extracting features approaches and discriminatory learning techniques.

For the purpose of identifying ageing face photos, Gong et al. [14] proposed the MEFD (Maximum Entropy Feature Descriptor) featured descriptor. It describes a discriminating trait.

A novel feature-matching approach called IFA (Identity Factor Analysis) is also suggested to improve identification accuracy.

For aging face identification, Ali et al.'s [9] focus was on combining form and texture characteristics. They used a particular form property of phasing alignment and the texture characteristic of LBP variation. Tandon et al.'s [15] effort at a unique method used the LBP of a specific area as ROI for recognizing elderly faces.

A unique face identification technique known as the Biview facial identification technique was described by Xiao et al. [16] and uses a mix of textural and form descriptors. Strategies for learning texture feature substructure are employed, and a graph is created for the shape topologies of face photos. The distinction (dissimilarity) between two histograms is determined using the chi-square analysis.

By utilising a bacteria-exploring fusion method, Yadav et al. [17] established a framework to enhance the outcomes of face detection during rising age. This method employed a mix of global and local face area features that were retrieved by LBP and bacterial feeding to lessen the impacts of ageing.

A discriminatory strategy for face validation across age development was put forth by Ling et al. [18]. This method divides pictures into two categories intra subject and inter subject by using SVM for categorization and GO (Gradient Orientation) and GOP (Gradient Orientation Pyramid) for feature identification.

A probability Eigen spatial framework-based Bayesian classification for age difference was proposed by Ramanathan & Chellappa [11]. When partners are divided into categories based on the age gaps between them.

Addressing these research gaps in synthetic face ageing using deep learning can lead to advancements in generating more realistic, diverse, and personalized aged faces, expanding the applications of this technology in various domains such as entertainment, forensics, and cosmetics.

Proposed Methodology

The proposed methodology for face ageing using CycleGAN presents an innovative approach to capturing and synthesizing realistic facial transformations. To begin, a comprehensive dataset is curated, comprising paired images of faces, where each pair includes an original image and its corresponding aged version. These images serve as the foundation for training the CycleGAN model. Through a combination of generator and discriminator networks, the model is trained to learn the intricate mapping between the input and output domains [19]. Additionally, a cycle-consistency loss function is employed to enforce the consistency between the forward and backward transformations, ensuring that the generated images maintain the integrity of the original features. This unique approach allows CycleGAN to effectively capture and simulate the subtle yet significant changes that occur during the ageing process [20]-[21]. By leveraging the learned mappings, the model is able to generate highly realistic and visually compelling age-progressed images, offering a valuable tool for a wide range of applications, including entertainment, the beauty industry, and even forensic investigations.

Dataset Description

The UTKFace dataset is a widely used and valuable resource for research and development in the field of computer vision, particularly in the domain of age estimation and facial analysis. It consists of a diverse collection of over 20,000 labeled face images, covering a wide range of ages, ethnicities, and genders. The dataset provides an extensive variation in age distribution, spanning from 0 to 116 years, making it an ideal choice for training and evaluating age estimation models. Each image in the UTKFace dataset is annotated with age, gender, and ethnicity information, offering rich and comprehensive metadata for conducting detailed analyses [22]-[23]. The dataset's diversity, large-scale nature, and accurate annotations make it an indispensable asset for studying age-related facial characteristics, developing age progression algorithms, and advancing the understanding of facial aging processes in diverse populations.

Figure 1: Sample Young and Old Images in Dataset

Preprocessing

Instance normalization plays a crucial role in face ageing using CycleGAN, a popular generative adversarial network framework. By applying instance normalization in this context, the network can effectively align and normalize the facial features across different age groups [24]. This normalization process ensures that the network focuses on capturing the essential ageing patterns rather than being influenced by unnecessary variations in lighting, pose, or expression. Consequently, instance normalization enables CycleGAN to learn more robust and meaningful mappings between young and aged faces, resulting in more accurate and visually convincing face ageing transformations.

Model Building

CycleGAN

CycleGAN has emerged as a powerful framework for face aging, revolutionizing the field of facial transformation. By leveraging the principles of generative adversarial networks and cycle consistency, CycleGAN enables the transformation of facial images between different age groups without the need for paired training data. Through its ability to learn a mapping from young to aged faces and vice versa, CycleGAN effectively captures and transfers the intricate facial details associated with aging, such as wrinkles, fine lines, and skin texture changes [25].

This approach not only facilitates the creation of realistic and natural-looking aged faces but also opens up possibilities for applications in entertainment, cosmetics, and even forensics, providing a versatile tool for exploring the complexities of face aging.

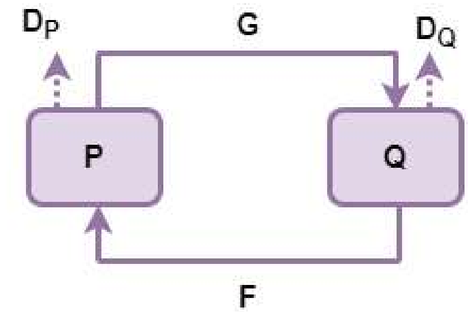


Figure 2: Framework of CycleGAN

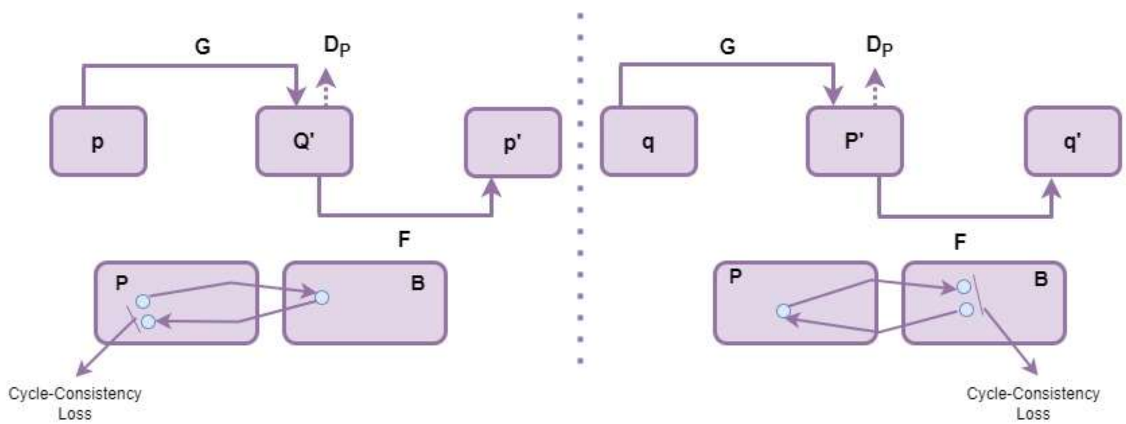


Figure.3: Cycle-Consistency in CycleGAN

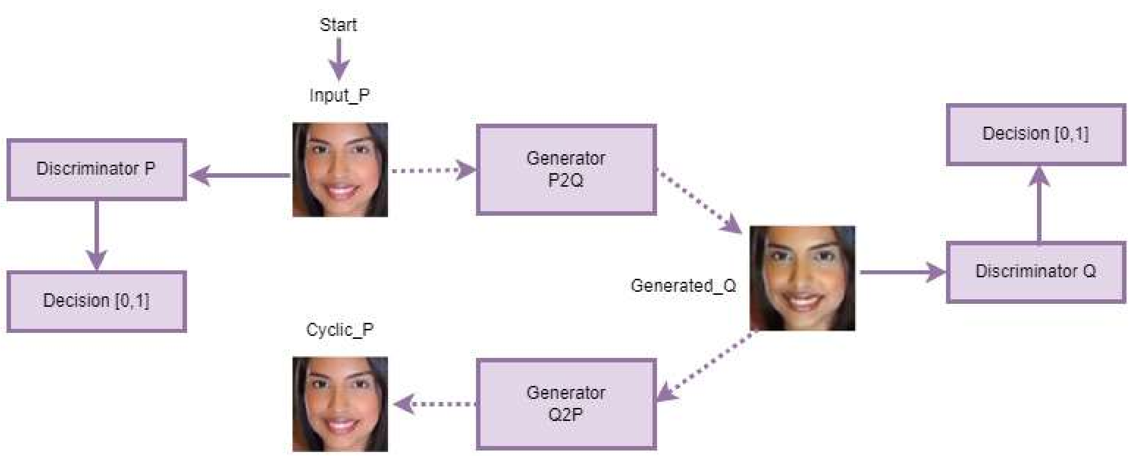


Figure 4: Process of Discriminator in CycleGAN

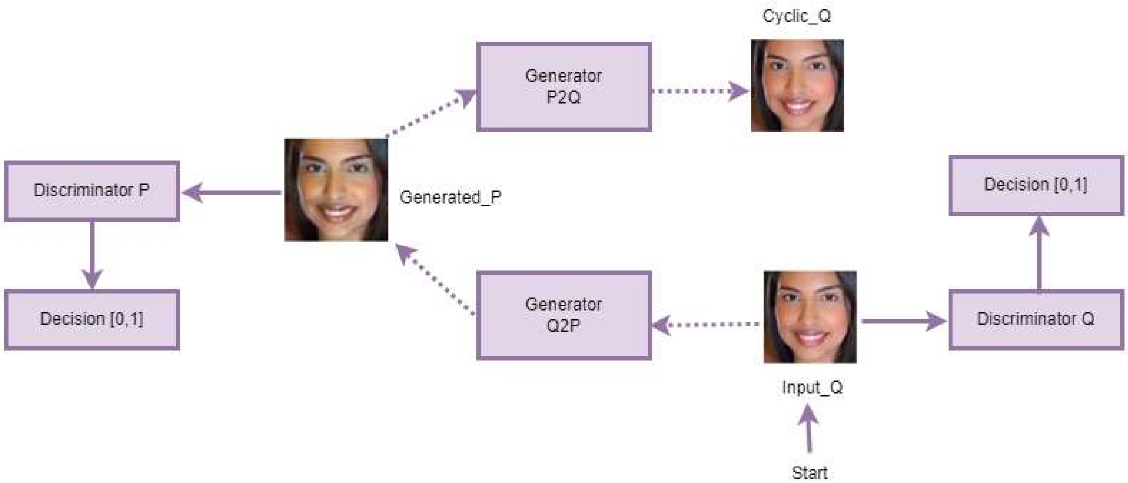


Figure 5: Process of Generator in CycleGAN

The CycleGAN was introduced by Zhu et al. [26] and allows maps to be learned from two celebrity image datasets without needing matched images. Incorporates a cycle consistency loss to acquire knowledge of the mappings without matched training examples. The mapping function has the following objective and initially uses the adversarial losses.

G: P → Q and its discriminator D_{Q} is

$$LGAN(G, D_{\mathrm{Q}}, \mathrm{P}, \mathrm{Q}) = E_{\mathrm{q} \sim Pdata(\mathrm{q})}[logD_{\mathrm{Q}}(\mathrm{q})] + E_{\mathrm{p} \sim Pdata(\mathrm{p})}[\log(1 - D_{\mathrm{Q}}(G(\mathrm{p})))] \quad 1$$

G create images G(p) that D won't be able to tell apart from real images q.

$$\mathrm{I} : \mathrm{Q} \sim \mathrm{P}$$

$$LGAN(\mathrm{I}, D_{\mathrm{P}}, \mathrm{Q}, \mathrm{P}) = E_{\mathrm{p} \sim Pdata(\mathrm{p})}[\log(D_{\mathrm{p}}(\mathrm{P})] + E_{\mathrm{q} \sim Pdata(\mathrm{q})}[\log(1 - D_{\mathrm{P}}(\mathrm{I}(\mathrm{p})))] \quad 2$$

Zhu et al. [6] introduce the cycle of continuous losses when adversarial loss cannot make sure that an input image will be converted into the desired field.

$$Lcyc(G, \mathrm{I}) = E_{\mathrm{p} \sim Pdata(\mathrm{p})}[\| F(G(\mathrm{p}) - \mathrm{p} \|_1)] + E_{\mathrm{q} \sim P(data(\mathrm{q}))}[\| \mathrm{I}(F(\mathrm{q}) - \mathrm{q} \|_1)] \quad 3$$

This is based on the forward cycle consistency principle: an input image X should look similar after being translated to Y and then returned to X

$$\mathrm{P} \rightarrow G(\mathrm{p}) \rightarrow \mathrm{I}(G(\mathrm{p})) \approx \mathrm{p}$$

Objective function is

$$L(G, \mathrm{I}, D_{\mathrm{p}}, D_{\mathrm{q}}) = LGAN(G, D_{\mathrm{q}}, \mathrm{P}, \mathrm{Q}) + LGAN(\mathrm{I}, D_{\mathrm{P}}, \mathrm{Q}, \mathrm{P}) + \lambda L_{cyc}(G, \mathrm{I}) \quad 4$$

Algorithm of Face-Ageing Using CycleGAN

Data Collection: Collect a UTKFace dataset of paired face images, where each pair consists of an original image and its corresponding aged version.

Preprocessing: Resize and normalize the images to a consistent size. Apply any necessary image transformations or augmentations.

Network Initialization: Initialize the generator networks (Generator P and Generator Q) and discriminator networks (Discriminator P and Discriminator Q) with random weights.

Training Loop: Iterate the following steps for a fixed number of epochs or until convergence:

a. Sample a batch of paired images from the dataset.

b. Forward Pass: Pass the original image through Generator P to generate an aged image. Similarly, pass the aged image through Generator Q to reconstruct the original image.

c. Calculate Adversarial Loss: Discriminator P evaluates the realism of the generated aged image, and Discriminator Q evaluates the realism of the reconstructed original image. Compute the adversarial loss by comparing the generated images with the corresponding real images.

d. Calculate Cycle-Consistency Loss: Compute the cycle-consistency loss by comparing the reconstructed original image with the original input image and the generated aged image with the corresponding aged input image.

e. Update Generator Networks: Backpropagate the total loss (combination of adversarial loss and cycle-consistency loss) and update the weights of Generator P and Generator Q using an optimizer (e.g., stochastic gradient descent).

f. Update Discriminator Networks: Backpropagate the adversarial loss separately for Discriminator P and Discriminator Q and update their weights using the optimizer.

Evaluation: Periodically evaluate the performance of the model using a validation set or qualitative analysis. Measure the training losses of Model.

Table 1: Summary of Discriminator

Layer (type)	Output Shape	Param #
input_2 (InputLayer)	[(None, 128, 128, 3)]	0
d_c1 (Conv2D)	(None, 64, 64, 64)	3136
lr1 (LeakyReLU)	(None, 64, 64, 64)	0
d_c3 (Conv2D)	(None, 32, 32, 256)	262400
iN3 (InstanceNormalization)	(None, 32, 32, 256)	512
lr3 (LeakyReLU)	(None, 32, 32, 256)	0
d_c4 (Conv2D)	(None, 16, 16, 512)	2097664
iN4 (InstanceNormalization)	(None, 16, 16, 512)	1024
lr4 (LeakyReLU)	(None, 16, 16, 512)	0
d_c5 (Conv2D)	(None, 16, 16, 1)	8193
Total params: 2,372,929		
Trainable params: 2,372,929		
Non-trainable params: 0		

Table 2: Summary of Generator

Layer (type)	Output Shape	Param #	Connected to

input_5 (InputLayer)	[(None, 128, 128, 3)]	0	[]
lambda_38 (Lambda)	(None, 134, 134, 3)	0	['input_5[0][0]']
g_e1_c (Conv2D)	(None, 128, 128, 64)	9472	['lambda_38[0][0]']
g_e1_bn (InstanceNormalization)	(None, 128, 128, 64)	128	['g_e1_c[0][0]']
activation_6 (Activation)	(None, 128, 128, 64)	0	['g_e1_bn[0][0]']
g_e2_c (Conv2D)	(None, 64, 64, 128)	73856	['activation_6[0][0]']
g_e2_bn (InstanceNormalization)	(None, 64, 64, 128)	256	['g_e2_c[0][0]']
activation_7 (Activation)	(None, 64, 64, 128)	0	['g_e2_bn[0][0]']
g_e3_c (Conv2D)	(None, 32, 32, 256)	295168	['activation_7[0][0]']
g_e3_bn (InstanceNormalization)	(None, 32, 32, 256)	512	['g_e3_c[0][0]']
activation_8 (Activation)	(None, 32, 32, 256)	0	['g_e3_bn[0][0]']
lambda_39 (Lambda)	(None, 34, 34, 256)	0	['activation_8[0][0]']
g_r1_c1 (Conv2D)	(None, 32, 32, 256)	590080	['lambda_39[0][0]']
g_r1_iN1 (InstanceNormalization)	(None, 32, 32, 256)	512	['g_r1_c1[0][0]']
lambda_40 (Lambda)	(None, 34, 34, 256)	0	['g_r1_iN1[0][0]']
g_r1_c2 (Conv2D)	(None, 32, 32, 256)	590080	['lambda_40[0][0]']
g_r1_iN2 (InstanceNormalization)	(None, 32, 32, 256)	512	['g_r1_c2[0][0]']
add_18 (Add)	(None, 32, 32, 256)	0	['g_r1_iN2[0][0]', 'activation_8[0][0]']
lambda_41 (Lambda)	(None, 34, 34, 256)	0	['add_18[0][0]']
g_r2_c1 (Conv2D)	(None, 32, 32, 256)	590080	['lambda_41[0][0]']
g_r2_iN1 (InstanceNormalization)	(None, 32, 32, 256)	512	['g_r2_c1[0][0]']
lambda_42 (Lambda)	(None, 34, 34, 256)	0	['g_r2_iN1[0][0]']
g_r2_c2 (Conv2D)	(None, 32, 32, 256)	590080	['lambda_42[0][0]']
g_r2_iN2 (InstanceNormalization)	(None, 32, 32, 256)	512	['g_r2_c2[0][0]']
add_19 (Add)	(None, 32, 32, 256)	0	['g_r2_iN2[0][0]', 'add_18[0][0]']
lambda_43 (Lambda)	(None, 34, 34, 256)	0	['add_19[0][0]']
g_r3_c1 (Conv2D)	(None, 32, 32, 256)	590080	['lambda_43[0][0]']
g_r3_iN1 (InstanceNormalization)	(None, 32, 32, 256)	512	['g_r3_c1[0][0]']

lambda_44 (Lambda)	(None, 34, 34, 256)	0	['g_r3_iN1[0][0]']
g_r3_c2 (Conv2D)	(None, 32, 32, 256)	590080	['lambda_44[0][0]']
g_r3_iN2 (InstanceNormalization)	(None, 32, 32, 256)	512	['g_r3_c2[0][0]']
add_20 (Add)	(None, 32, 32, 256	0	['g_r3_iN2[0][0]', 'add_19[0][0]']
lambda_45 (Lambda)	(None, 34, 34, 256)	0	['add_20[0][0]']
g_r4_c1 (Conv2D)	(None, 32, 32, 256)	590080	['lambda_45[0][0]']
g_r4_iN1 (InstanceNormalization)	(None, 32, 32, 256)	512	['g_r4_c1[0][0]']
lambda_46 (Lambda)	(None, 34, 34, 256)	0	['g_r4_iN1[0][0]']
g_r4_c2 (Conv2D)	(None, 32, 32, 256	0	['lambda_46[0][0]']
g_r4_iN2 (InstanceNormalization)	(None, 32, 32, 256)	590080	['g_r4_c2[0][0]']
add_21 (Add)	(None, 32, 32, 256)	512	['g_r4_iN2[0][0]', 'add_20[0][0]']
lambda_47 (Lambda)	(None, 34, 34, 256)	0	['add_21[0][0]']
g_r5_c1 (Conv2D)	(None, 32, 32, 256)	590080	['lambda_47[0][0]']
g_r5_iN1 (InstanceNormalization)	(None, 32, 32, 256)	512	['g_r5_c1[0][0]']
lambda_48 (Lambda)	(None, 34, 34, 256)	0	['g_r5_iN1[0][0]']
g_r5_c2 (Conv2D)	(None, 32, 32, 256)	0	['lambda_48[0][0]']
g_r5_iN2 (InstanceNormalization)	(None, 32, 32, 256)	590080	['g_r5_c2[0][0]']
add_22 (Add)	(None, 32, 32, 256)	512	['g_r5_iN2[0][0]', 'add_21[0][0]']
lambda_49 (Lambda)	(None, 34, 34, 256)	0	['add_22[0][0]']
g_r6_c1 (Conv2D)	(None, 32, 32, 256)	590080	['lambda_49[0][0]']
g_r6_iN1 (InstanceNormalization)	(None, 32, 32, 256)	512	['g_r6_c1[0][0]']
lambda_50 (Lambda)	(None, 34, 34, 256)	0	['g_r6_iN1[0][0]']
g_r6_c2 (Conv2D)	(None, 32, 32, 256)	0	['lambda_50[0][0]']
g_r6_iN2 (InstanceNormalization)	(None, 32, 32, 256)	590080	['g_r6_c2[0][0]']
add_23 (Add)	(None, 32, 32, 256)	512	['g_r6_iN2[0][0]' 'add_22[0][0]']
lambda_51 (Lambda)	(None, 34, 34, 256)	0	['add_23[0][0]']
g_r7_c1 (Conv2D)	(None, 32, 32, 256)	590080	['lambda_51[0][0]']
g_r7_iN1 (InstanceNormalization)	(None, 32, 32, 256)	512	['g_r7_c1[0][0]']
lambda_52 (Lambda)	(None, 34, 34, 256)	0	['g_r7_iN1[0][0]']

g_r7_c2 (Conv2D)	(None, 32, 32, 256)	0	['lambda_52[0][0]']
g_r7_iN2 (InstanceNormalization)	(None, 32, 32, 256)	590080	['g_r7_c2[0][0]']
add_24 (Add)	(None, 32, 32, 256)	512	['g_r7_iN2[0][0]', 'add_23[0][0]']
lambda_53 (Lambda)	(None, 34, 34, 256)	0	['add_24[0][0]']
g_r8_c1 (Conv2D)	(None, 32, 32, 256)	590080	['lambda_53[0][0]']
g_r8_iN1 (InstanceNormalization)	(None, 32, 32, 256)	512	['g_r8_c1[0][0]']
lambda_54 (Lambda)	(None, 34, 34, 256	0	['g_r8_iN1[0][0]']
g_r8_c2 (Conv2D)	(None, 32, 32, 256)	0	['lambda_54[0][0]']
g_r8_iN2 (InstanceNormalization)	(None, 32, 32, 256)	590080	['g_r8_c2[0][0]']
add_25 (Add)	(None, 32, 32, 256)	512	['g_r8_iN2[0][0]', 'add_24[0][0]']
lambda_55 (Lambda)	(None, 34, 34, 256)	0	['add_25[0][0]']
g_r9_c1 (Conv2D)	(None, 32, 32, 256)	590080	['lambda_55[0][0]']
g_r9_iN1 (InstanceNormalizatio	(None, 32, 32, 256)	512	['g_r9_c1[0][0]']
lambda_56 (Lambda)	(None, 34, 34, 256)	0	['g_r9_iN1[0][0]']
g_r9_c2 (Conv2D)	(None, 32, 32, 256)	295040	['lambda_56[0][0]']
g_r9_iN2 (InstanceNormalization)	(None, 32, 32, 256)	256	['g_r9_c2[0][0]']
add_26 (Add)	(None, 32, 32, 256)	0	['g_r9_iN2[0][0]', 'add_25[0][0]']
g_d1_dc (Conv2DTranspose)	(None, 64, 64, 128)	737992	['add_26[0][0]']
g_d1_bn (InstanceNormalization)	(None, 64, 64, 128)	128	['g_d1_dc[0][0]']
activation_9 (Activation)	(None, 64, 64, 128)	0	['g_d1_bn[0][0]']
g_d2_dc (Conv2DTranspose)	(None, 128, 128, 64)	0	['activation_9[0][0]']
g_d2_bn (InstanceNormalization)	(None, 128, 128, 64)	9411	['g_d2_dc[0][0]']
activation_10 (Activation)	(None, 128, 128, 64)	0	['g_d2_bn[0][0]']
lambda_57 (Lambda)	(None, 134, 134, 64)	0	['activation_10[0][0]']
g_pred_c (Conv2D)	(None, 128, 128, 3)	9472	['lambda_57[0][0]']
activation_11 (Activation)	(None, 128, 128, 3)	0	['g_pred_c[0][0]']
Total params: 11,388,675			
Trainable params: 11,388,675			

Non-trainable params: 0

Result Analysis

The images of famous faces are from a public source. The dataset was then separated into two categories such as young and Old based on the metadata of the face images. Young individuals make up the initial category, whereas older individuals in their late years make up the second. Then, we built and stated the proposed model employing the open-source PyTorch CycleGAN network. Additionally, the proposed model was given to PyTorch's default training. After exporting the training model to a file, the prepared model is tested by loading it from the face images. We have trained the model for slightly over 100 epochs. In this study, the final results of the proposed model have been drawn at different epochs 5, 3, and 2. Table 1 and Table 2 show the number of epochs and training time of young-to-old and old-to-young models.

Table 1: Number of Epochs and Training Time of Young-to-old Model

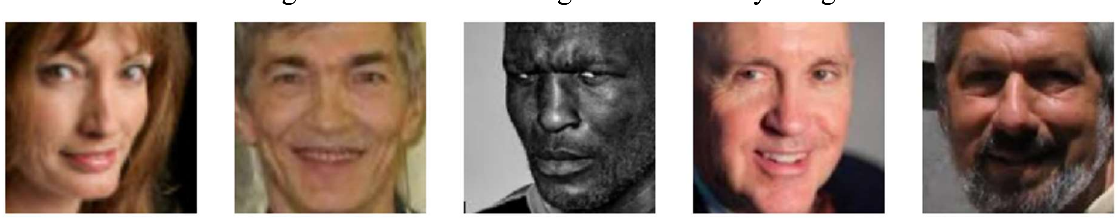
No of Epoch	Time
5	24 ms
3	20 ms
2	22 ms

Table 2: Number of Epochs and Training Time of old-to-young Model

No of Epoch	Time
5	33 ms
3	22 ms
2	22 ms

↓↓↓↓↓↓↓↓↓↓↓↓↓↓↓ YOUNG TO OLD ↓↓↓↓↓↓↓↓↓↓↓↓↓↓↓↓

Figure 6: Result of Young to Old celebrity images



↓↓↓↓↓↓↓↓↓↓↓↓↓↓↓ Old to Young ↓↓↓↓↓↓↓↓↓↓↓↓↓↓↓

Figure 7: Result of Old to Young celebrity images

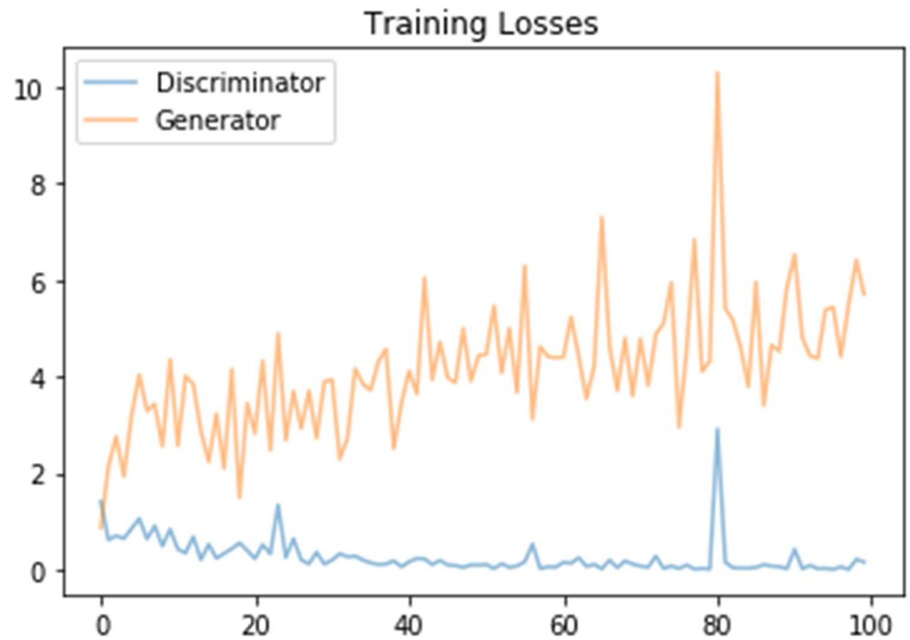


Figure 8: Training Losses of Discriminator and Generator

Figure 8 shows the training Losses of Discriminator and Generator. During the initial stages of training, the discriminator loss is expected to be high as the discriminator is learning to differentiate between real and generated faces. As the generator improves its ability to generate more realistic aged faces, the discriminator loss starts to decrease since it becomes more challenging for the discriminator to distinguish between real and generated samples.

Conclusion and Future Scope

Using the UTKFace dataset, we transformed young celebrity face images into old face celebrity images based on CycleGAN deep learning model. The purpose of the study was to reduce the time complexities of the training model while still producing high-quality old-aged developed face images from young faces of celebrities. The suggested model is based on GAN and is controlled using cycle consistency loss. Since the face images of celebrities produced by the proposed model can be more real, they have a better aging affect than the standard models for several of the experiments. The training losses of the discriminator and generator are often visualized using line plots or graphs. The graph of training losses over time provides valuable insights into the learning dynamics, convergence, and overall performance of the CycleGAN model for face aging. By monitoring and analyzing these losses, researchers and practitioners can fine-tune the model, adjust hyperparameters, or introduce regularization techniques to enhance the quality of generated aged faces and ensure a stable training process.

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