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by Aryan Mehta

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Department of Electrical Engineering, IIT Jodhpur

BTP Report

<u>November 2020</u>

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Title: Face Aging using Identity Preserved conditional Generative Adversarial Network

Names & Roll Numbers: **1.** Aryan Mehta(B17EE012)
2. Asif Ahmed(B17EE013)

Name of Supervisor: **1.** Dr. Himanshu Kumar

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Abstract

Face aging as we know it in today's world has many applications such as Entertainment purpose, cross age face verification to find missing children, or missing person in general. But since it is not possible to generalize a face for different people at a particular age because of lack of organized data of same person in sequential age. So, we aim to generate an aged face in an age group instead of a particular age. We also know that there are many challenges faced in this process, foremost is to preserve the identity of a person while simultaneously ageing it.
By grouping people into different age groups, we transfer average features of target age to the face to be aged.

So, we implement the Identity Preserved Conditional GANs. **We further improvise by categorizing the faces based on Gender**, and determine how this affects the original algorithm.
In the algorithm conditional generative adversarial network generates the target age conditioned face for input image and the identity preserving res-net model preserves the input face features.

Motivation

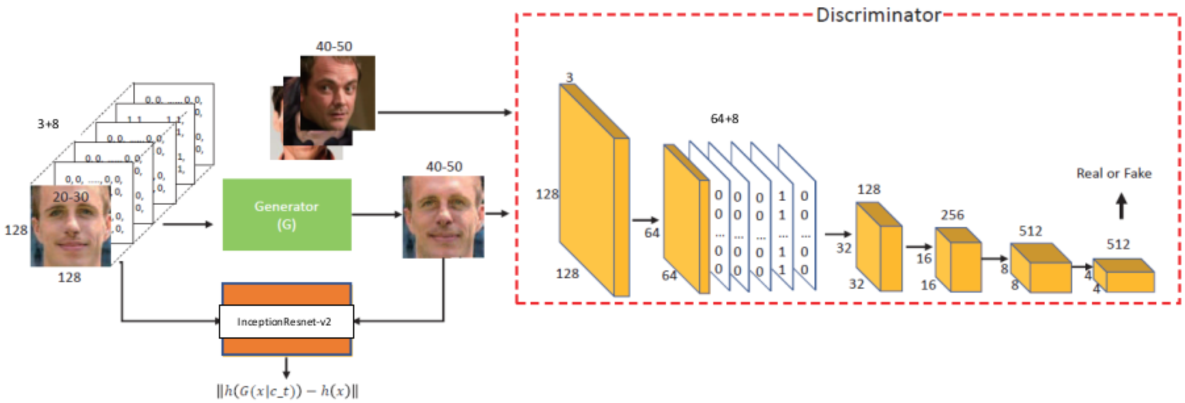
The pre-existing models for face aging use different approaches such as prototype based as in people are classified into different age groups and an average face for each age is obtained and thus the difference between these average faces of different groups is used as the aging pattern, which does the job of face aging but the obtained image is not realistic. One other such technique is the one in which aging patterns in physical features like hair color, wrinkles, etc. are observed and learned with a parametric model which is in turn very lengthy and time-consuming task.
Thus, to overcome all the difficulties, we choose to implement the identity preserving model which performs better task at generating images with target age and is time efficient to train.

The major concern in determining the aging pattern that we understood is that it differs based on gender and ethnicity. So, to address that problem, only use of age condition is not enough so we implement our model based on these conditions also.

We observed that in young age region the features of male and female are very similar, to overcome that providing an extra condition of gender improved the model.

Methodology

Our Model:



Conditional Generative Adversarial Model:

The generative adversarial model consists of two parts,

This cGAN model takes an input image and target age, and generate aged face in target age group.

To make the Adversarial network model conditional we feed the condition (age and gender) as an additional layer in the input to both discriminator and generator model

a. Generator model

   The generator model forms a relation from prior noise distribution to the data space.

   Mathematical representation for generator loss,

$$\mathbf{L_G=1/2(E_{y\sim p(y)})[D(G(y|C_t)-1)^2]} \qquad \text{---(1)}$$

b. Discriminator model

This discriminator model gives the probability and determines whether input to discriminator is from generator(fake) or a real image.

Mathematical representation of discriminator loss,

$$\mathbf{L_D=1/2(E_{x\sim p(x)})[(D(x|C_t)-1)^2] + 1/2(E_{y\sim p(y)})[(D(G(y|C_t))^2] + L_{age}} \qquad \text{----(2)}$$

$$\mathbf{L_{age} = \sum_{x\epsilon p(x)} l(G(x|C_t),C_t)} \qquad \text{----(3)}$$

where, x→input image, Ct→ Target condition(age+gender)

y→real faces in target condition group, D(x|Ct)→probability that x belongs to real face group, this should be high

G(y|Ct)→generated image {1-D(G(y|Ct))}→probability that generated image lies in real image set of target condition.

l(.)→softmax loss term for difference actual generated age and target age.

c. Identity Preserving InceptionRes-net model:

Since the generator loss alone cannot constitute towards preserving identity as it only guides the input image towards target condition, and the generated image may look like anyone in the target group, so to preserve identity and make the generated image look realistic we use lower feature layers(they store content of the image) from extracted layers by resnet based feature extractor.

The mathematical expression for perceptual loss,

$$\mathbf{L_{identity}= \sum_{x\epsilon p(x)} || h(x)-h(G(x|C_t)) ||^2} \qquad \text{---(4)}$$

where,

h(.)→features extracted by chosen feature layer(lower layer)

$L_{identity}$→perceptual loss

The overall generator loss can be obtained by combining eqn. (1) and (4):

$\mathbf{L_{generator} = L_G + L_{identity}}$

$\mathbf{L_{discriminator} = L_D}$

Implementation:

We used the preprocessed imdb-wiki dataset(60000 images) with age and gender labels for the training purpose, we take age and gender condition and classify them into 10 groups. The learning rate for IPCGAN is set to 0.001 and a batch size of 10 images is used with total of 1000000 steps for IPCGAN training.

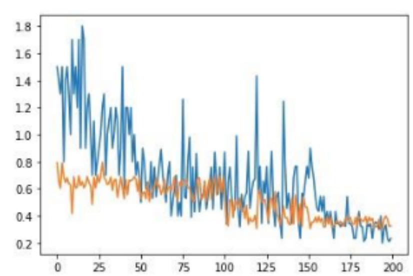
Results:

It can be observed that in the loss graph after applying the identity preservation model the loss decreases significantly, indicating that result has improved and generated image is identifiable to input image.

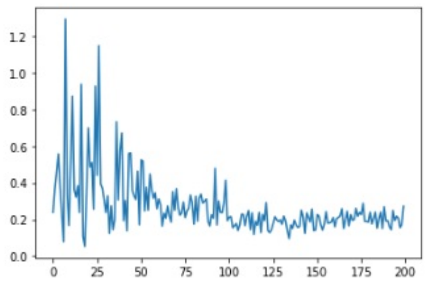
Loss graph:

blue→generator loss vs Epochs,

orange→discriminator loss vs Epochs



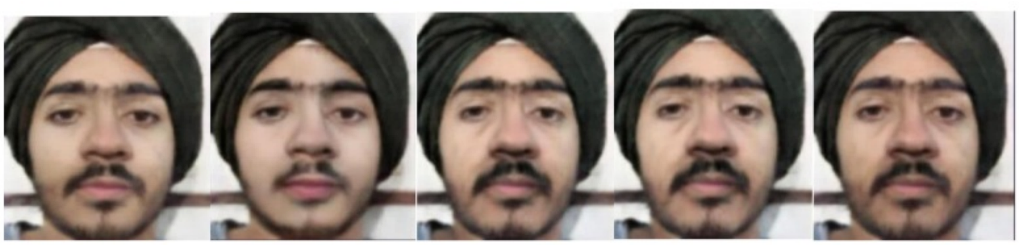
Generator loss after identity preservation vs Epochs

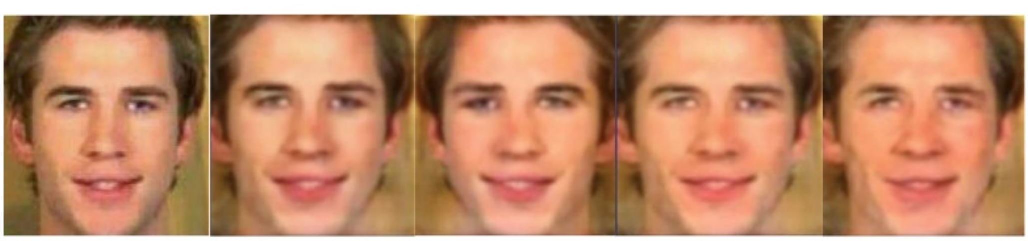


Our model's results:

Below results show that our model competes with already existing state of art methods and outperforms them in several aspects ,importantly when looking at generated image it is identifiable as the input image.

Input 10-20 20-40 40-50 50+





Our Model

CAAE & acGAN

Our Model

CAAE & acGAN

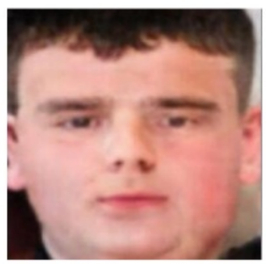
Improvement result:

<u>**There is a recognizable feature difference when we give target condition as a female v/s male which confirms the improvement in the model.**</u>

Much better result could have been achieved, if a better dataset could be made keeping in mind the feature similarity in faces in the young age region by adding a large number of images in region of 10-30 years.

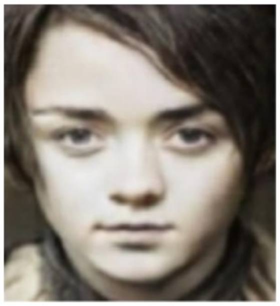
Target=Female

Target=Male



Target=Female

Target=Male

Conclusion and Future Scope:

In recent years there have been tremendous research in finding feasible method to generate images, GANs have been a major breakthrough in that as they allow us to effectively generate realistic images. In this project we successfully implemented a variation of it, that is conditional Generative Adversarial Network with age conditions, and combined it with identity preserving InceptionResNet-v2 model**. We introduced the Gender condition to shape the model to better learn the aging pattern.**

Further Scope of improvement is that we can introduce the ethnicity factor to better predict the aging pattern and generate good quality images.

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