Improved GAN with Anti-Spoofing Detection

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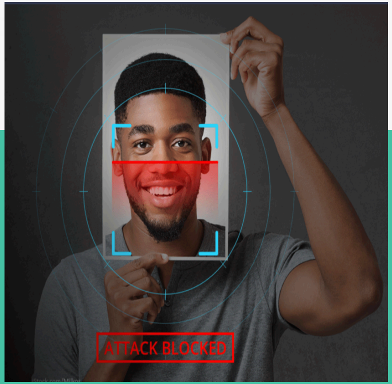
Outline

Part I

Introduction



Part II

Dataset

Part III

Method Analysis

Part IV

Results

Part I　Introduction

Introduction

- It is prevalent to authorize a transaction using our biometric information, including fingerprints and facial features.
- Sometimes, a detection system cannot receive high-resolution input image in real life because of damaged cameras or terrible weather.
- An updated method is proposed to solve the face-spoofing problem in this project.

Modified Algorithm

modified the PULSE in

https://arxiv.org/abs/2003.03808

Liveness Detection Model

https://github.com/zeusees/HyperFAS
https://arxiv.org/pdf/1604.02878.pdf

The LPIPS Standard

https://arxiv.org/abs/1801.03924

Part II Dataset

FairFace: Face Attribute Dataset for Balanced Race, Gender, and Age.
https://arxiv.org/abs/1908.04913

FairFace contains 108,501 images with faces of different race, gender and age, which ensures the accuracy of the results.

FairFace Prediction

race: East Asian
race4: Asian
gender: Female
age: 30-39

FairFace Prediction

race: Latino_Hispanic
race4: Asian
gender: Female
age: 30-39

FairFace Prediction

race: Black
race4: Black
gender: Male
age: 3-9

Part III Method Analysis

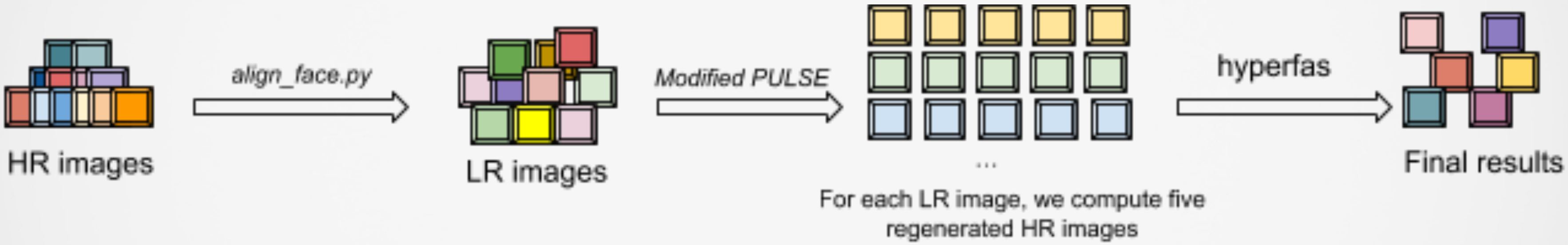
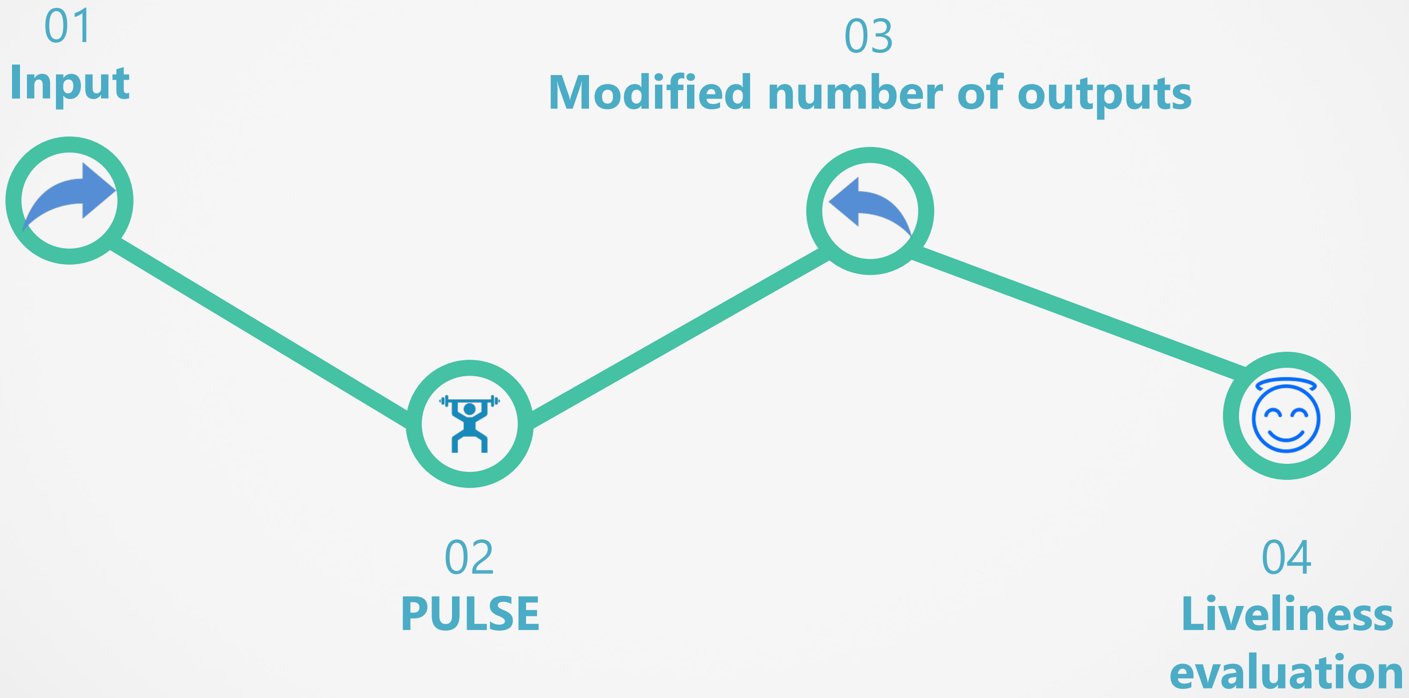


Figure: The demonstration of the overall model in the project

Method Analysis Steps



01 Input

1 **Run align_face.py**

Sending the HR (High Resolution) images from FairFace dataset as the input.

2 **After align_face.py**

Images would be scaled into the same size with faces locating in relatively the same position before they are downscaled and outputted, which provided the perfect simulation of LR (Low Resolution) pictures for our model to use.

02 PULSE

- PULSE is for Self-Supervised Photo Upsampling via Latent Space Exploration of Generative Models appeared in https://arxiv.org/abs/2003.03808.

- It is an algorithm based on latent space and to obtain the final output by traversing the HR (High Resolution) image manifold and searching for the original LR (Low Resolution) input.

03 Modified Number of Outputs

- In the PULSE algorithm, a set of feasible pictures would be produced with a given value (referred to epsilon)
- The final output image would be chosen from the intersection between the set and the natural image manifold, but the result created in this way could be random, biased and sometimes not realistic.
- In our model, we modified the parameter of PULSE so that the algorithm could generate HR images five times instead of one time in the original experiment.

04 Liveliness Evaluation

- We use the model in https://www.arxiv-vanity.com/papers/1905.02244/ and https://github.com/zeusees/HyperFAS to pick the most “real” face among the five outputs.

Part IV Results

Evaluation Method: LPIPS

We use the LPIPS as the evaluation metric to know about the similarity of two pictures. LPIPS stands for Learned Perceptual Image Patch Similarity (LPIPS) appeared in https://arxiv.org/pdf/1801.03924.pdf .

Implementation of LPIPS

- LPIPS illustrates a stable and consistent assessment for trained CNN even when facing some distorting types.
- LPIPS measures the distance between images. The higher the score is, the more different the pictures are.

Results Comparison

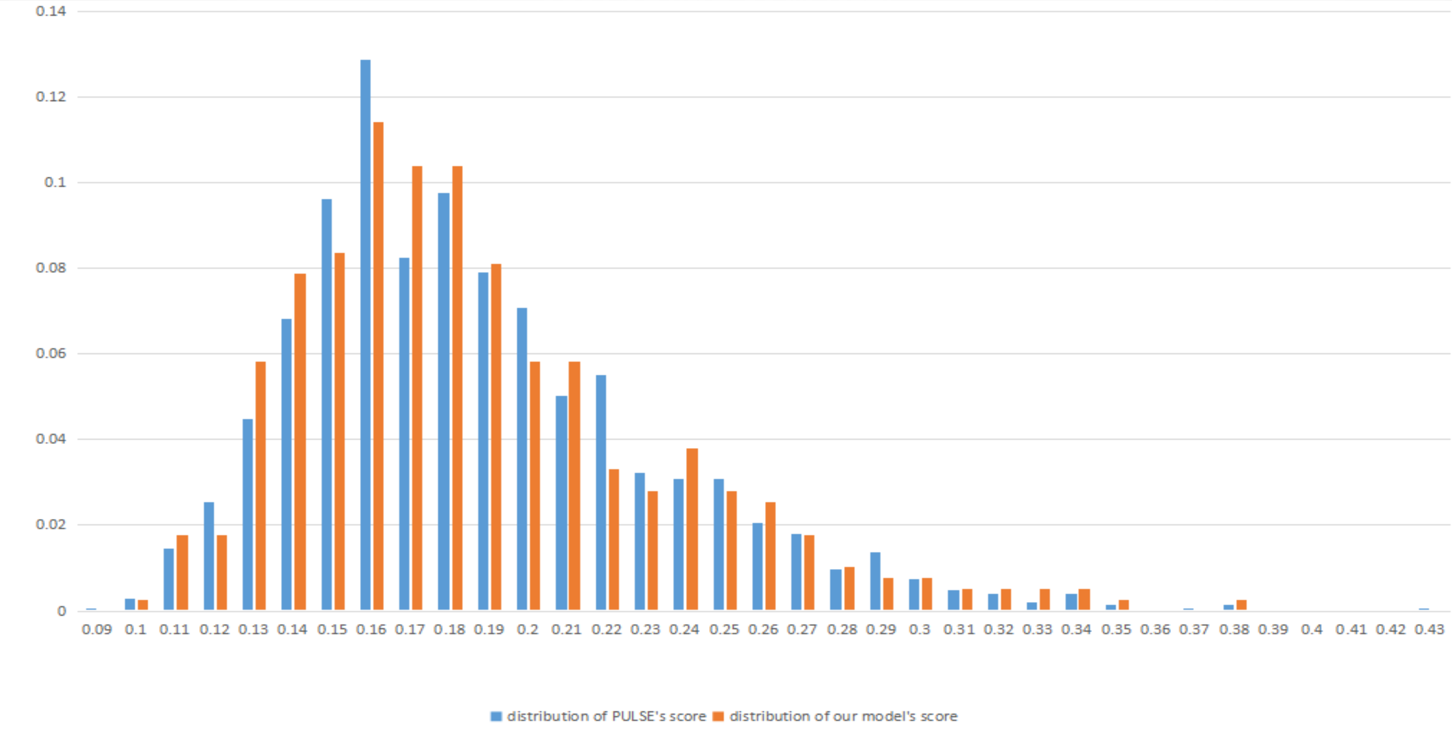
	PULSE	Our model
LPIPS score	0.19213	0.19175

	PULSE	Our model
Expected number of outputs	7595	1519
Actual number of outputs	1453	394
Production rate	19.13%	25.94%

We calculated the average of all the LPIPS scores among the outputs. Comparing with the original model, the LPIPS score has improved slightly.

The reliability of production has increased, which means not only the outputted images would be more realistic, but also the probability of receiving a rational outcome would grow up.

Results Comparison



The figure demonstrates the comparison of two distributions of PULSE and our model.

Thanks !