Learning Face Age Progression: A Pyramid Architecture of GANs (CVPR 2018)
Yang et al.

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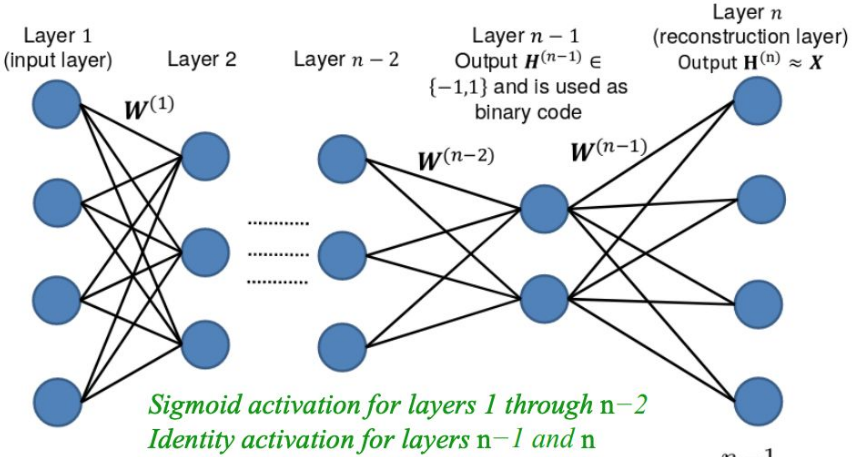
Learning to Hash with Binary Deep Neural Network

- "Unsupervised Hashing with BDNN (UH-BDNN)"



$$\min_{\mathbf{W},\mathbf{c},\mathbf{B}} J = \frac{1}{2m}\left\|\mathbf{X} - \mathbf{W}^{(n-1)}\mathbf{B} - \mathbf{c}^{(n-1)}\mathbf{1}_{1\times m}\right\|^2 + \frac{\lambda_1}{2}\sum_{l=1}^{n-1}\left\|\mathbf{W}^{(l)}\right\|^2$$

$$+\frac{\lambda_2}{2m}\left\|\mathbf{H}^{(n-1)} - \mathbf{B}\right\|^2 + \frac{\lambda_3}{2}\left\|\frac{1}{m}\mathbf{H}^{(n-1)}(\mathbf{H}^{(n-1)})^T - \mathbf{I}\right\|^2 + \frac{\lambda_4}{2m}\left\|\mathbf{H}^{(n-1)}\mathbf{1}_{m\times 1}\right\|^2$$

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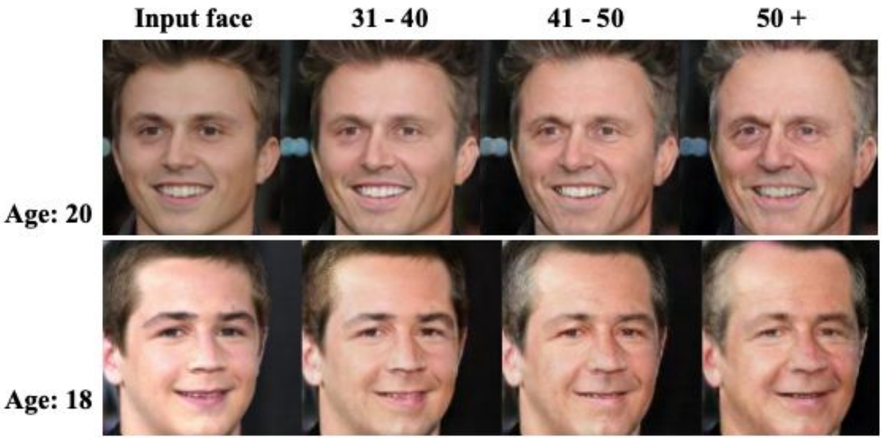
Introduction

Two underlying requirements of face age progression

- Aging accuracy
- Identity permanence



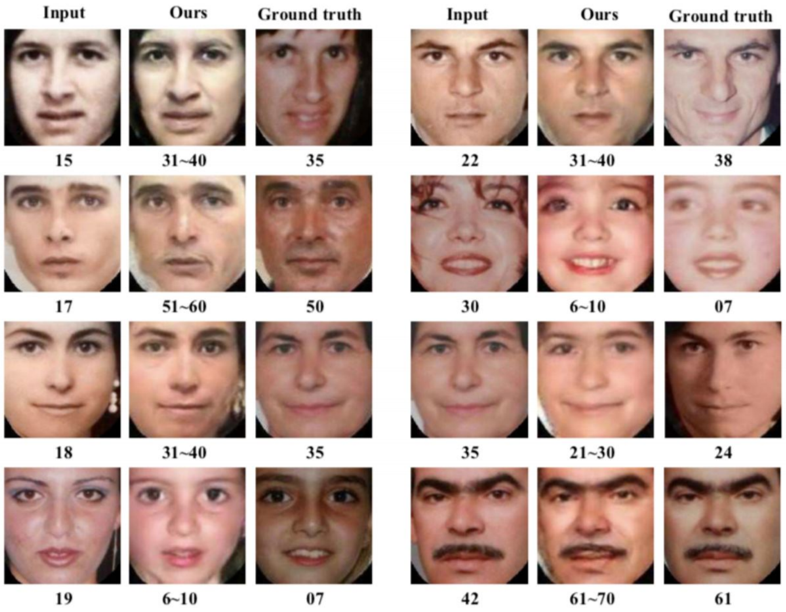
Problems with previous methods

Current deep generative network based methods focus more on the modeling face transformation between two age groups

- Good aging accuracy
- Poor identity permanence

Also, require multiple images of different ages of the same person

Cropped facial area



Operated on cropped faces
Ignoring forehead and hair

It is essential to operate age progression on the entire face.

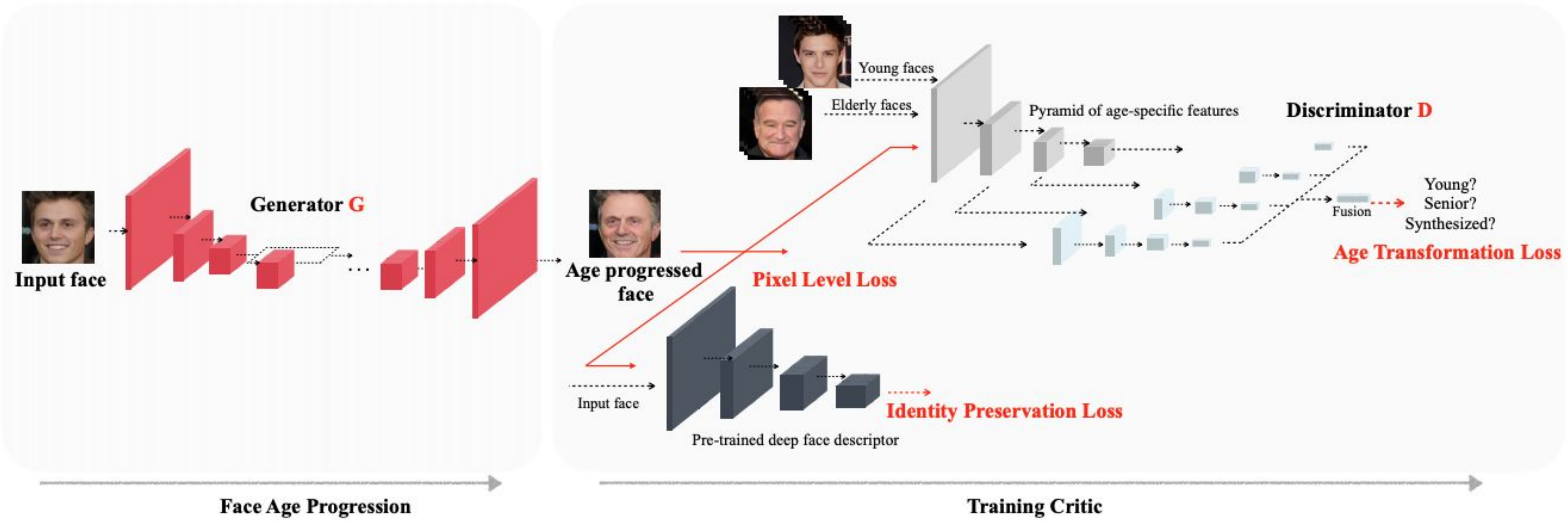
Age progression/regression by conditional auto encoder Zhang et al.

Contributions

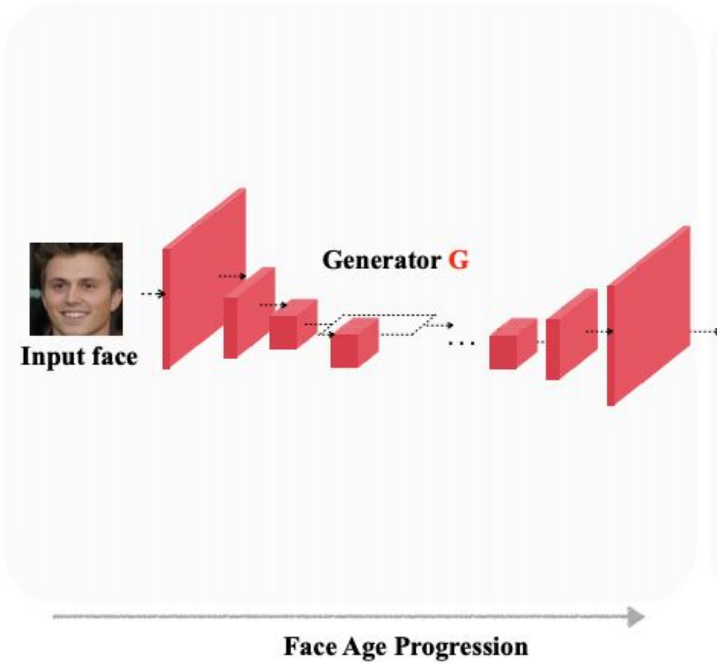
A novel GAN based approach which give high aging accuracy while preserving personal identities

It also operates with full face including forehead and hair which are ignored in other studies

Pyramid Architecture of GAN



Generator



- Synthesizing aged face require only forward pass through Generator
- 3 conv layer
  - Encode it to latent space, capture stable facial properties
- 4 residual blocks
  - Modeling the common structure shared by input and output faces
- 3 Deconv layer
  - Age transformation to target image space

Discriminator

Classic GAN D loss

$$\mathcal{L}_{GAN\_D} = -\mathbb{E}_{x \in P_{young}(x)} \log[1 - D(G(x))] - \mathbb{E}_{x \in P_{old}(x)} \log[D(x)]$$

- In practice, D converges faster than Generator
- This cause feeding vanishing gradient to Generator

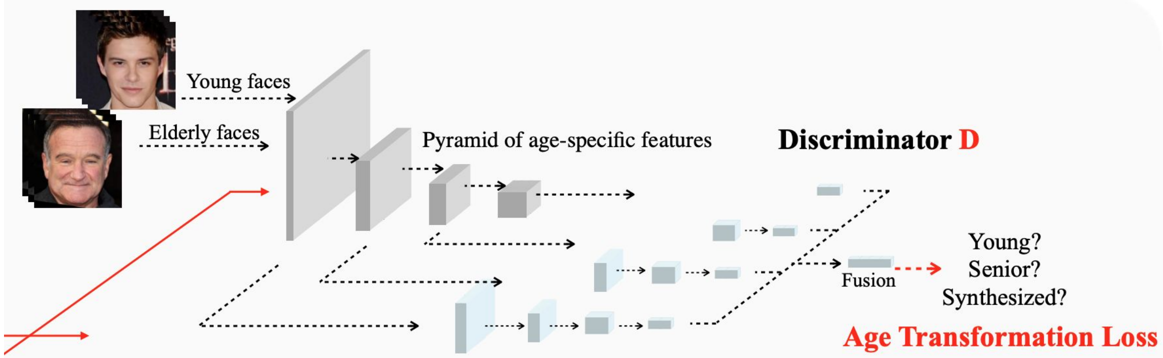
Loss

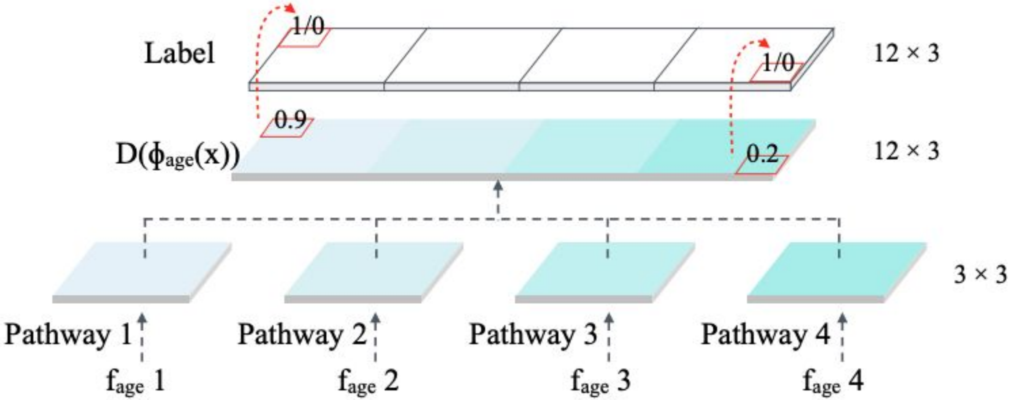
$$\mathcal{L}_{GAN\_D} = \frac{1}{2}\mathbb{E}_{x\sim P_{old}(x)}[(D_\omega(\phi_{age}(x)) - 1)^2] + \frac{1}{2}\mathbb{E}_{x\sim P_{young}(x)}[D_\omega(\phi_{age}(G(x)))^2 + D_\omega(\phi_{age}(x))^2] \tag{3}$$

$$\mathcal{L}_{GAN\_G} = \mathbb{E}_{x\sim P_{young}(x)}[(D_\omega(\phi_{age}(G(x))) - 1)^2] \tag{4}$$

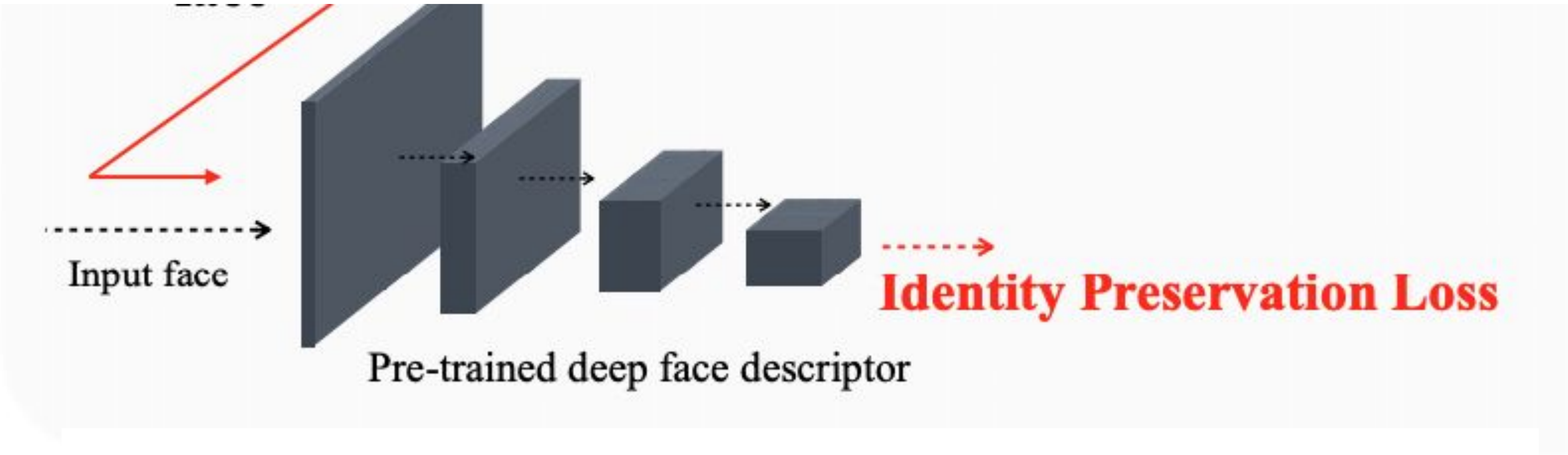
ϕ_{age} : extracting age-related feature, make the generated face more distinguishable from the true elderly face

Joint estimation





Identity Preservation



$$\mathcal{L}_{identity} = \mathbb{E}_{x \in P_{young}(x)} d(\phi_{id}(x), \phi_{id}(G(x)))$$

Objective

Pixel wise L2 loss

$$\mathcal{L}_{pixel} = \frac{1}{W \times H \times C} \|G(x) - x\|_2^2$$

The system training loss

$$\mathcal{L}_G = \lambda_a \mathcal{L}_{GAN\_G} + \lambda_p \mathcal{L}_{pixel} + \lambda_i \mathcal{L}_{identity}$$

$$\mathcal{L}_D = \mathcal{L}_{GAN\_D}$$

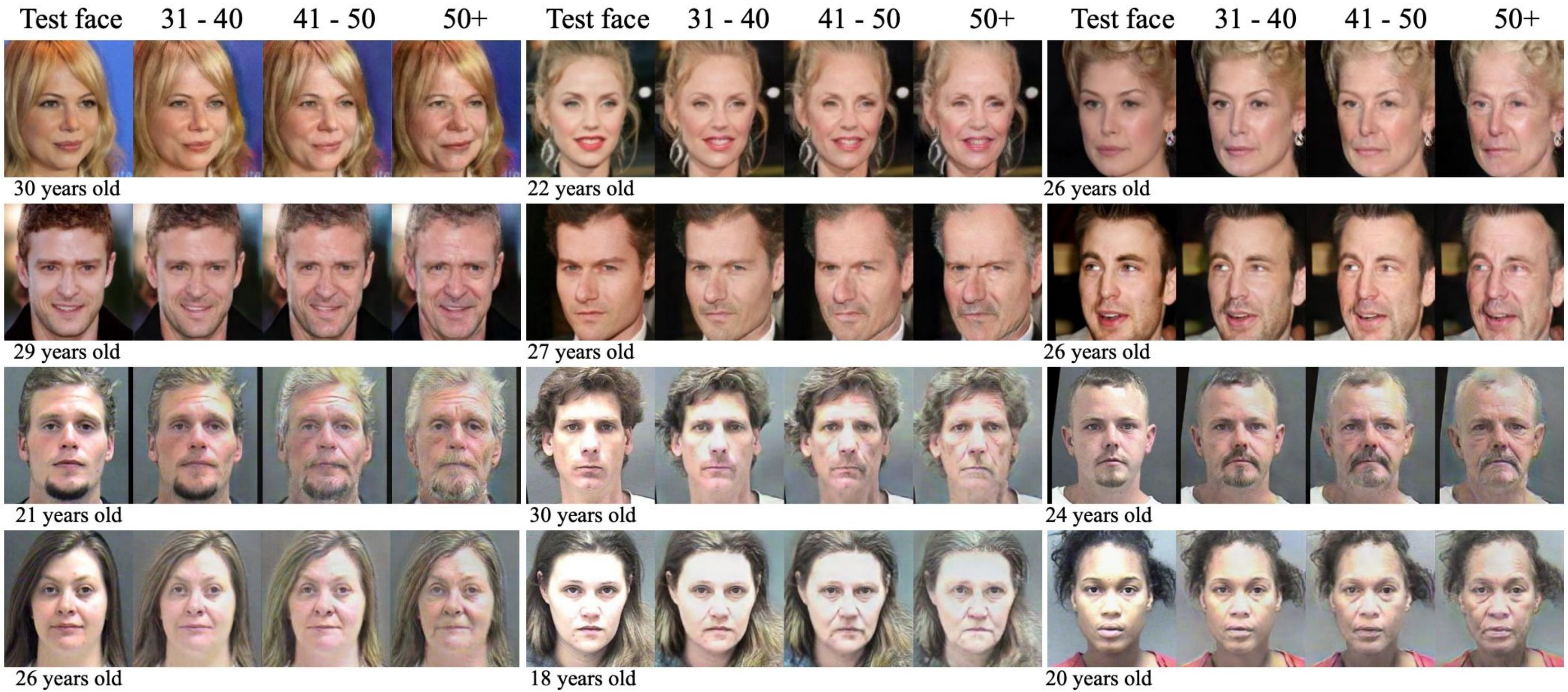
Experiment & results

Experiment I: Age progression

Experiment II: Aging Model Evaluation

- II-A: Visual fidelity
- II-B: Aging Accuracy
- II-C: Identity Preservation
- II-D: contribution of Pyramid architecture
- II-E: Comparison with previous work

Experiment I: Age progression



Experiment II-A: Visual Fidelity

(a) Robustness to glasses, occlusion and pose variations.

(b) Hair aging.

(c) Facial detail preservation.

① forehead wrinkles
② eyes
③ mouth
④ beard
⑤ laugh lines

(d) Aging consistency.

Experiment II-B: Aging Accuracy

MORPH				CACD			
Age Cluster 0	**Age Cluster 1**	**Age Cluster 2**	**Age Cluster 3**	**Age Cluster 0**	**Age Cluster 1**	**Age Cluster 2**	**Age Cluster 3**
	Synthesized faces*				Synthesized faces*		
–	42.84 ± 8.03	50.78 ± 9.01	59.91 ± 8.95	–	44.29 ± 8.51	48.34 ± 8.32	52.02 ± 9.21
–	42.84 ± 0.40	50.78 ± 0.36	59.91 ± 0.47	–	44.29 ± 0.53	48.34 ± 0.35	52.02 ± 0.19
	Natural faces				Natural faces		
32.57 ± 7.95	42.46 ± 8.23	51.30 ± 9.01	61.39 ± 8.56	38.68 ± 9.50	43.59 ± 9.41	48.12 ± 9.52	52.59 ± 10.48

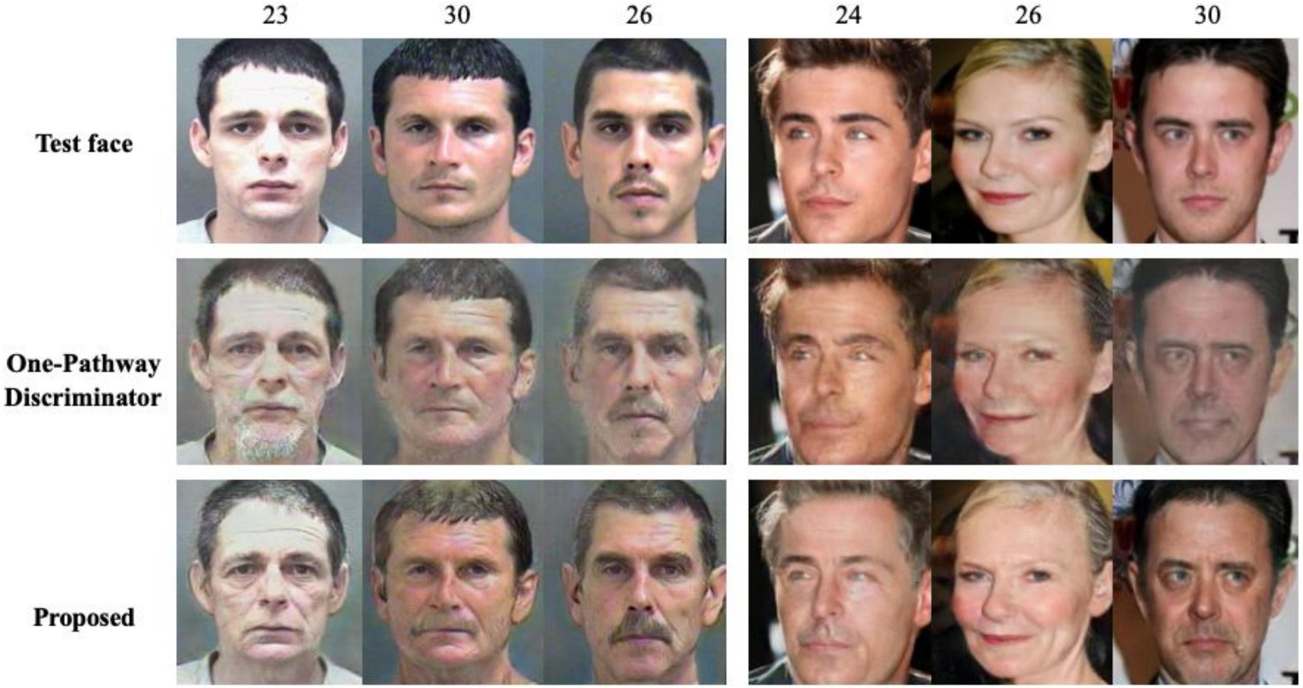
Experiment II-C: Identity Preservation

Table 2. Objective face verification results on (a) MORPH and (b) CACD

		Aged 1	Aged 2	Aged 3
(a)		verification confidence[a]		
	Test face	94.64 ± 0.03	91.46 ± 0.08	85.87 ± 0.25
	Aged 1	–	94.34 ± 0.06	89.92 ± 0.30
	Aged 2	–	–	92.23 ± 0.24
		verification confidence [b]		
	Test face	94.64 ± 1.06	91.46 ± 3.65	85.87 ± 5.53
	Aged 1	–	94.34 ± 1.64	89.92 ± 3.49
	Aged 2	–	–	92.23 ± 2.09
		verification rate (threshold = 76.5, FAR = 1e - 5)		
	Test face	100 ± 0 %	98.91 ± 0.40 %	93.09 ± 1.31 %

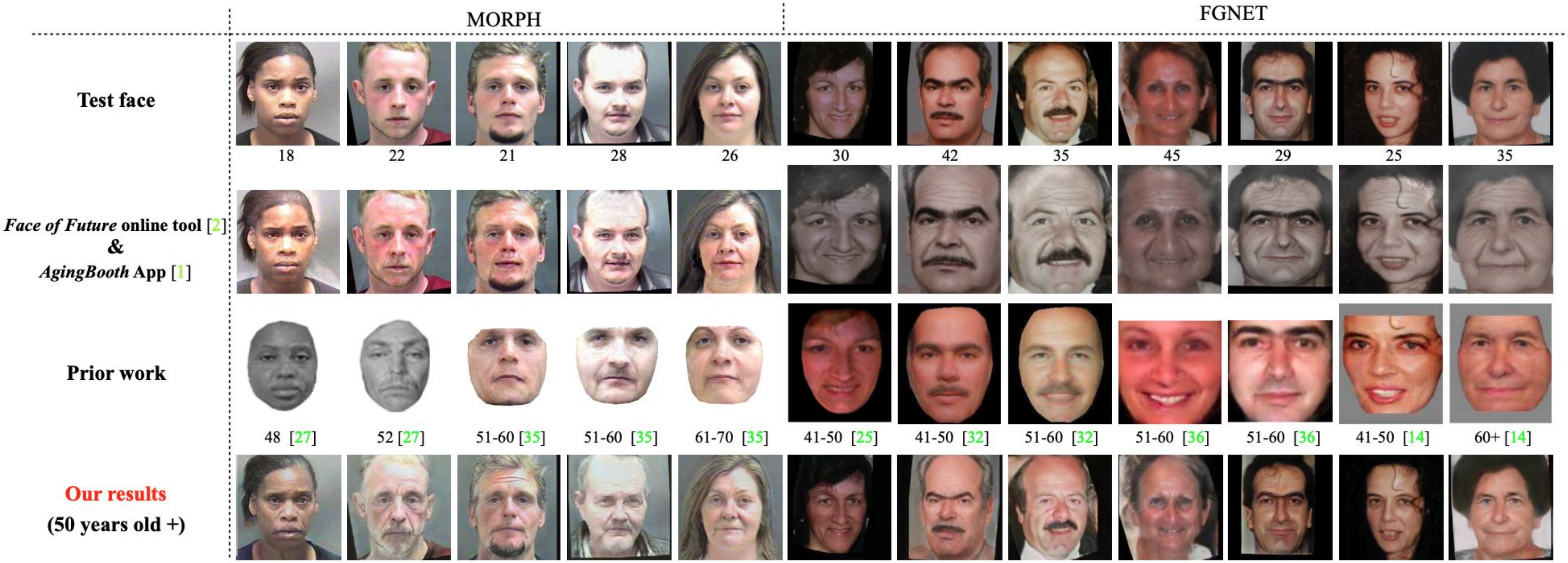
		Aged 1	Aged 2	Aged 3
(b)		verification confidence[a]		
	Test face	94.13±0.04	91.96±0.12	88.60±0.15
	Aged 1	–	94.88±0.16	92.63±0.09
	Aged 2	–	–	94.21±0.24
		verification confidence[b]		
	Test face	94.13±1.19	91.96±2.26	88.60±4.19
	Aged 1	–	94.88±0.87	92.63±2.10
	Aged 2	–	–	94.21±1.25
		verification rate (threshold = 76.5, FAR = 1e - 5)		
	Test face	99.99 ± 0.01 %	99.91 ± 0.05 %	98.28 ± 0.33 %

Experiment II-D: Contribution of pyramid architecture



(a) MORPH (b) CACD

Experiment II-E: Comparison with previous work



Conclusion

Achieving higher aging accuracy while identity preservation compare to previous works.

Pyramid Architecture of GAN was introduced to generate more details of aging.

Thank You!

Quiz

1. Which component of the network was designed with pyramid architecture
    A. Generator
    B. Discriminator
    C. Identity Preservation

2. Which one is not the major component of age progression

    A. Aging accuracy
    B. Identity permanence
    C. Gender distinguishing