AGE GAP REDUCER-GAN FOR RECOGNIZING AGE-SEPARATED FACES

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MOTIVATION

- Building age-invariant face recognition algorithms beneficial in applications such as locating missing persons, homeland security, and passport services
- Challenges: Personalized aging pattern depending on numerous factors including ethnicity, environmental conditions, and stress level as well as limited availability of labeled databases
- Two categories for approaches for matching faces with age progression:
 - Discriminative: Finding the age-invariant signatures from the input faces and use it for the recognition task.
 - Generative: Inducing the changes in the input facial images to incorporate aging variations and projecting the images at a common age
- Generative adversarial networks (GANs) are being utilized to generate synthetic images using convolutional neural nets (CNNs). Different GAN based approaches have been proposed for facial age simulation [1, 2]

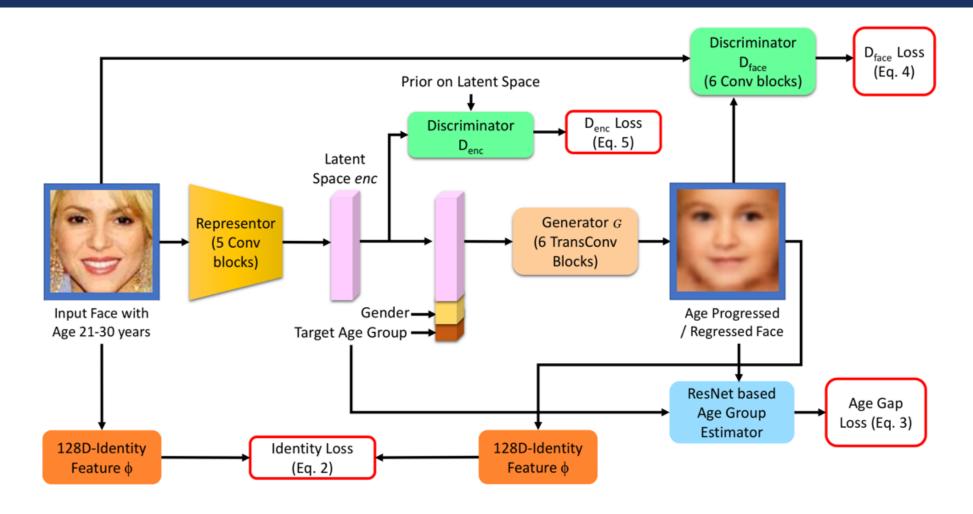
^[2] Yang et al., "Learning face age progression: A pyramid architecture of GANs," in IEEE CVPR, 2018, pp. 31–39.

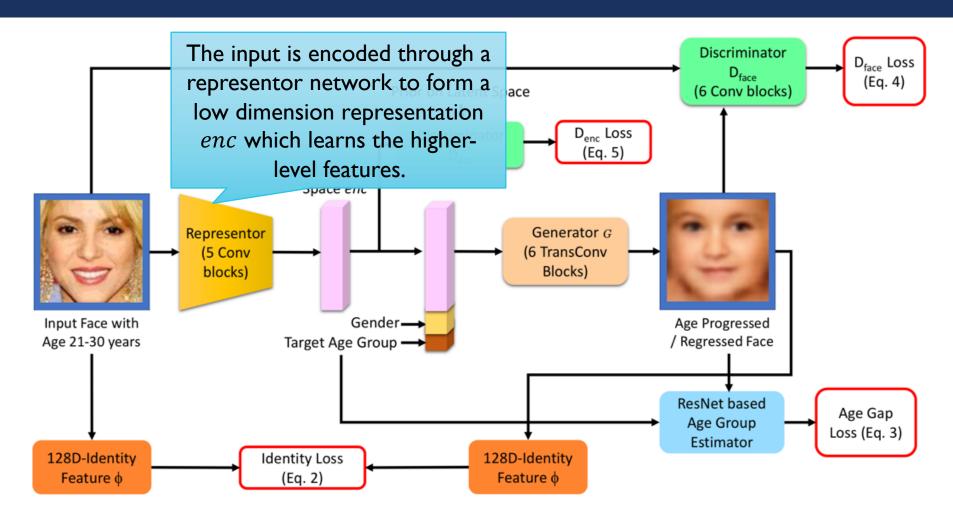
CHALLENGES OF EXISTING FACE AGING APPROACHES

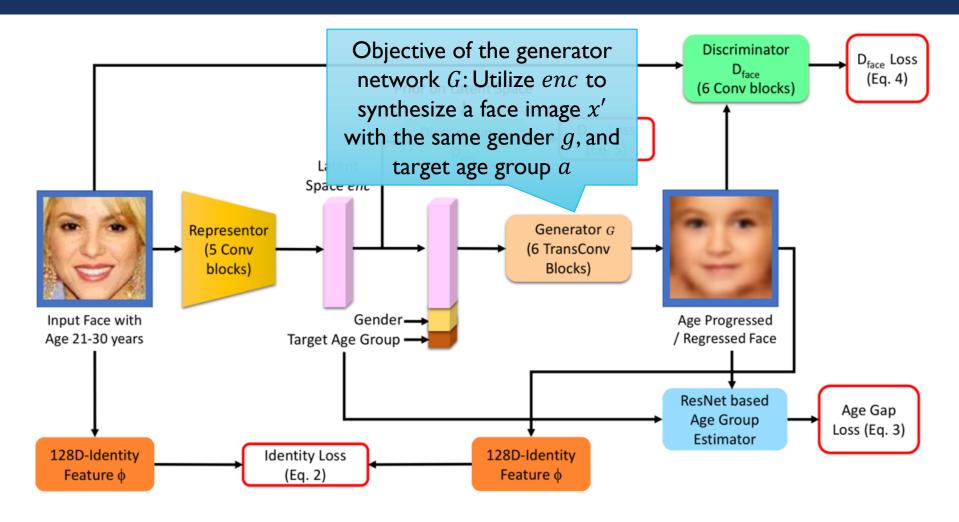
- Majority of existing GANs based research related to facial aging focus only on generating images for different age groups
- Most of these techniques do not demonstrate their efficacy in enhancing the face recognition accuracy of ageseparated probe and gallery face images
- Only some of these techniques can produce both age-progressed as well as age-regressed faces and very few of them cater to both young as well as old age groups

RESEARCH CONTRIBUTIONS

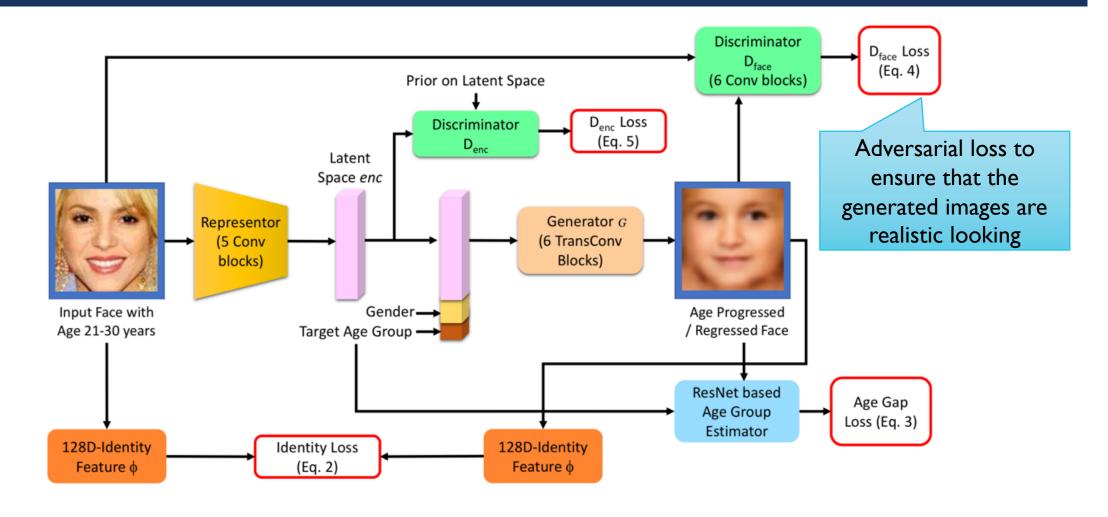
- Introducing AGR-GAN: Uses a multi-task discriminator that is able to progress/regress the age of an input face to a target age group
- Incorporating an identity preserving feature which ensures that the generated (regressed/progressed) face image has the same identity representation as the input face image
- Performing joint learning of the age group estimator module with the image generation. This novel architecture eliminates the need for paired age-labeled data in the training phase
- Demonstrating the efficacy of the proposed AGR-GAN on three publicly available facial aging databases for the problem of age-separated face recognition

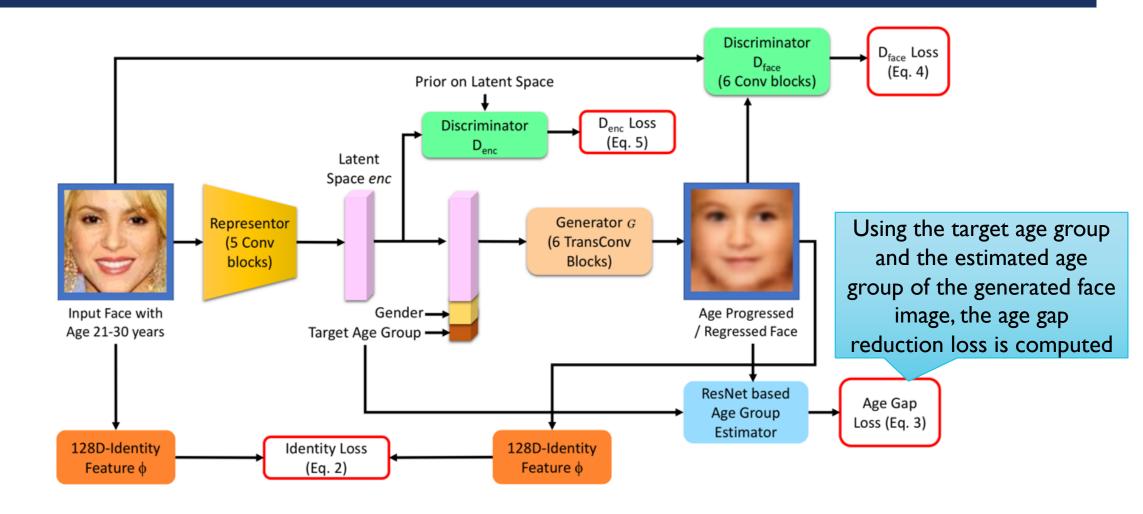


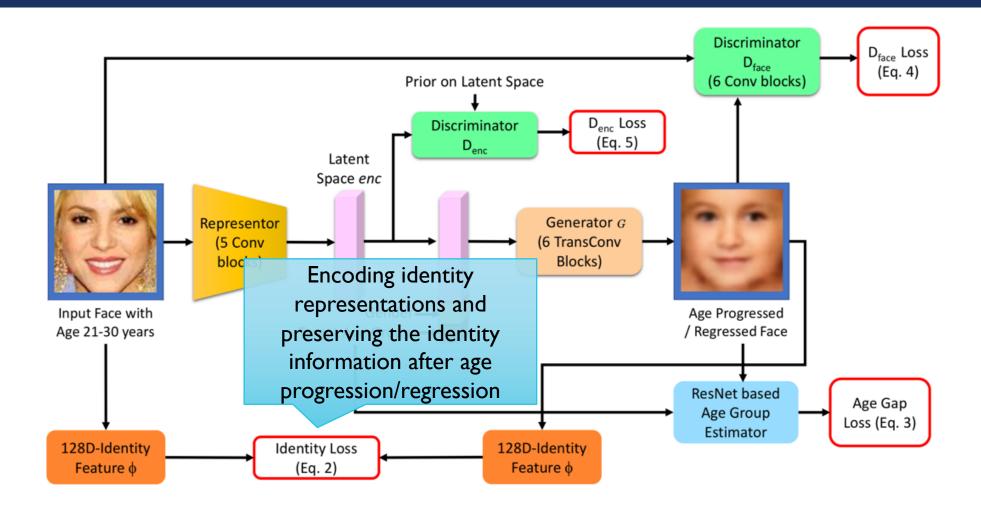


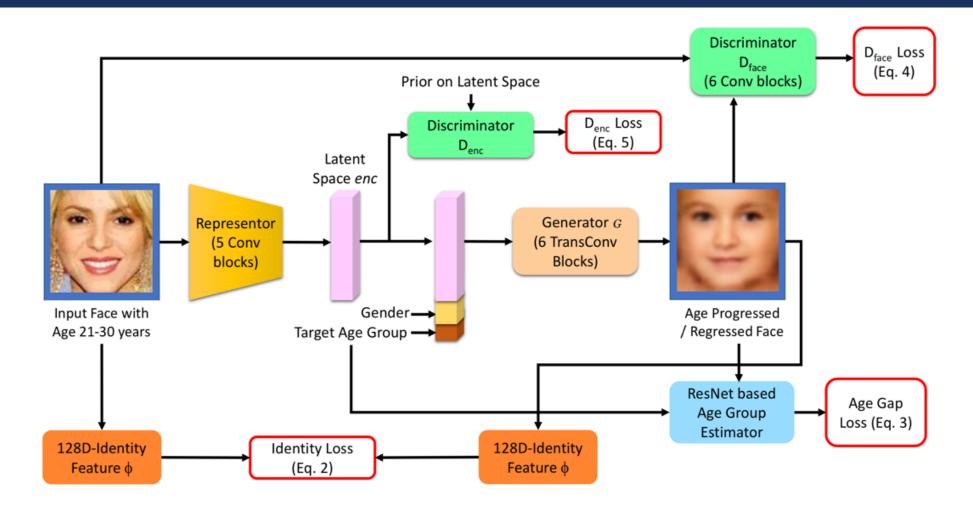


Adversarial loss on enc to PROPOSED AGR-GAN ensure it is uniformly distributed, thus, leading to Discriminator smooth age transformations D_{face} Loss D_{face} (Eq. 4) **Prior on Latent Space** (6 Conv blocks) $\mathsf{D}_{\mathsf{enc}}$ Loss Discriminator (Eq. 5) $\mathsf{D}_{\mathsf{enc}}$ Latent Space enc Generator G Representor (6 TransConv (5 Conv blocks) Blocks) Input Face with Gender-Age Progressed / Regressed Face Age 21-30 years Target Age Group -ResNet based Age Gap Age Group Loss (Eq. 3) Estimator 128D-Identity 128D-Identity **Identity Loss** Feature ϕ (Eq. 2) Feature ϕ

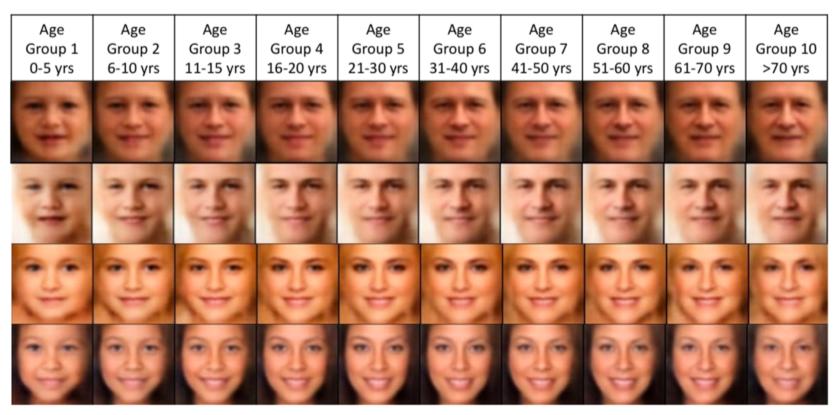








EXPERIMENTAL RESULTS: VISUAL FIDELITY



- Age Progression
- Sample generated outputs by the proposed AGR-GAN across age groups

- The proposed AGR-GAN is able to learn the aging patterns across different age groups as well as maintain the identity information across different synthesis outputs of the same subject
- Able to model the aging patterns even with varying facial hair, gender, and ethnicity.

EXPERIMENTAL RESULTS: AGE-SEPARATED FACE RECOGNITION

Increase in FaceNet model-based face recognition by using faces generated from the AGR-GAN. 'Per-DB SOTA' refers to the state-of-the-art performance reported on the databases.

Database	Metric	Per-DB SOTA	Only FaceNet	FaceNet + AGR- GAN
MORPH	Rank-I	93.60 [1]	94.03	94.15
CACD-VS	Accuracy @ FPR=0.1%	91.10 [1]	97.50	98.39
CALFW	Accuracy @ FPR=0.1%	86.50 [2]	57.50	87.15

 For all three databases, it is observed that utilizing AGR-GAN outputs with FaceNet increases the age-separated face matching performance

^[1] Li et al., "Distance metric optimization driven convolutional neural network for age invariant face recognition," Pattern Recognition, vol. 75, pp. 51–62, 2018.

^[2] Zheng et al., "Cross-age LFW: A database for studying cross-age face recognition in unconstrained environments," CoRR, vol. abs/1708.08197, 2017.

EXPERIMENTAL RESULTS: AGING MODEL EVALUATION

Age estimation (years) of faces generated by the proposed AGR-GAN.

Age Group (Age Range)	MORPH	CACD- VS	CALFW
I (0-5)	5.26	8.45	6.79
2 (6-10)	12.18	11.32	12.38
3 (11-15)	14.32	15.09	14.23
4 (15-20)	17.65	18.94	19.36
5 (21-30)	29.22	27.13	22.71
6 (31-40)	33.51	39.10	35.13
7 (41-50)	47.20	42.59	41.36
8 (51-60)	54.19	53.72	58.75
9 (61-70)	63.69	68.24	63.84
10 (>70)	69.85	74.32	78.38

- Critical to evaluate the ability of the proposed model to produce face images with the targeted age group
- Apart from age group I (age range 0-5 years), age group 2 (age range 6-10 years), and age group I0 (age range > 70 years), the mean age of GAN generated faces in all other age groups follows the expected trend
- The divergence in the values of age groups 1,
 2, and 10 may be attributed to lesser number of face images in the training set

Thanks!