Supplementary Material for BlendFace: Re-designing Identity Encoders for Face-Swapping

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Figure 1: **Architecture of our model.** We simply add a convolution and sigmoid layer to the last layer of the original attribute encoder from AEI-Net [7].

A. Architecture

Here, we detail the architecture of our face-swapping model. As described in the main paper, our architecture is based on AEI-Net [7] but we incorporate a mask predictor into the model inspired by previous studies [12, 13, 15]. We illustrate the architecture of our model in Fig. 1. We simply add a convolution layer and sigmoid layer to the last layer of the attribute encoder to predict blending masks \hat{M} . We blend the foreground face image $\tilde{Y}_{s,t}$ and target image X_t using the predicted \hat{M} as follows:

$$Y_{s,t} = \tilde{Y}_{s,t} \odot \hat{M} + X_t \odot (1 - \hat{M}). \tag{1}$$

In our model, we assume the blending masks for the same target images should be the same independently of source images. Note that losses are computed on the blended result $Y_{s,t}$; therefore, the intermediate generated face $\tilde{Y}_{s,t}$ is noisy outside of the face.

B. Comparison with Additional Baselines

We compare our model with two additional baselines in Fig. 2: 1) We input masked source images into a pretrained face-swapping model that is the same model as Arc-Arc in Fig. 6, denoted as *Masked Infer.*. To only include the face area below the eyebrow and between ears, we generate the



Figure 2: Comparison with additional baselines.

masks by computing the convex hull of 68 facial landmarks by FAN [1]. 2) We train Arc-Arc model from scratch with masked source images, denoted as *Masked Train*. As can be seen, the models still suffer from the attribute inconsistency. Therefore, we can conclude our method is a unique solution for the attribute leakage problem.



Figure 3: Different models and dataset.

C. Attribute Biases on Different Face Recognition Models

We visualize the similarity distributions of different face recognition models in Fig. 3: (a) CurricularFace (Cur) [5], (b) QMagFace (QMag) [11], (c) AdaFace (Ada) [6] on a

lager dataset WebFace12M (WF12M) [17], (d) ArcFace (Arc) on GAN-generated face images (Syn) [9], and (e) ArcFace with VisionTransformer (ViT) [3]. We can see that the attribute leakage problem still exists in these various face recognition models. Additionally, we train ViT backbone using our BlendFace pretraining. As shown in Fig. 3 (f), our training strategy works well even on ViT, which proves the generality of our method.

D. More Comparisons on FF++

We show more qualitative comparisons on FaceForensics++ [10] in Fig. 4. Our model performs consistent faceswapping for a range of source and target images compared to previous methods [2, 4, 8, 12, 14, 16].

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Figure 4: More comparisons on FF++.