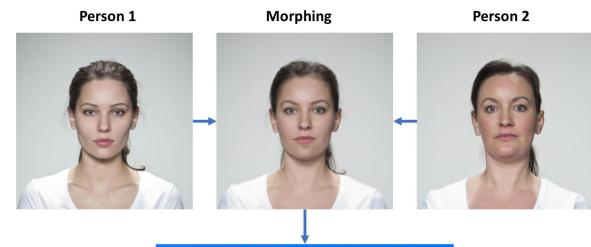
Towards Generalizable Morph Attack Detection with Consistency Regularization

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Problem Statement

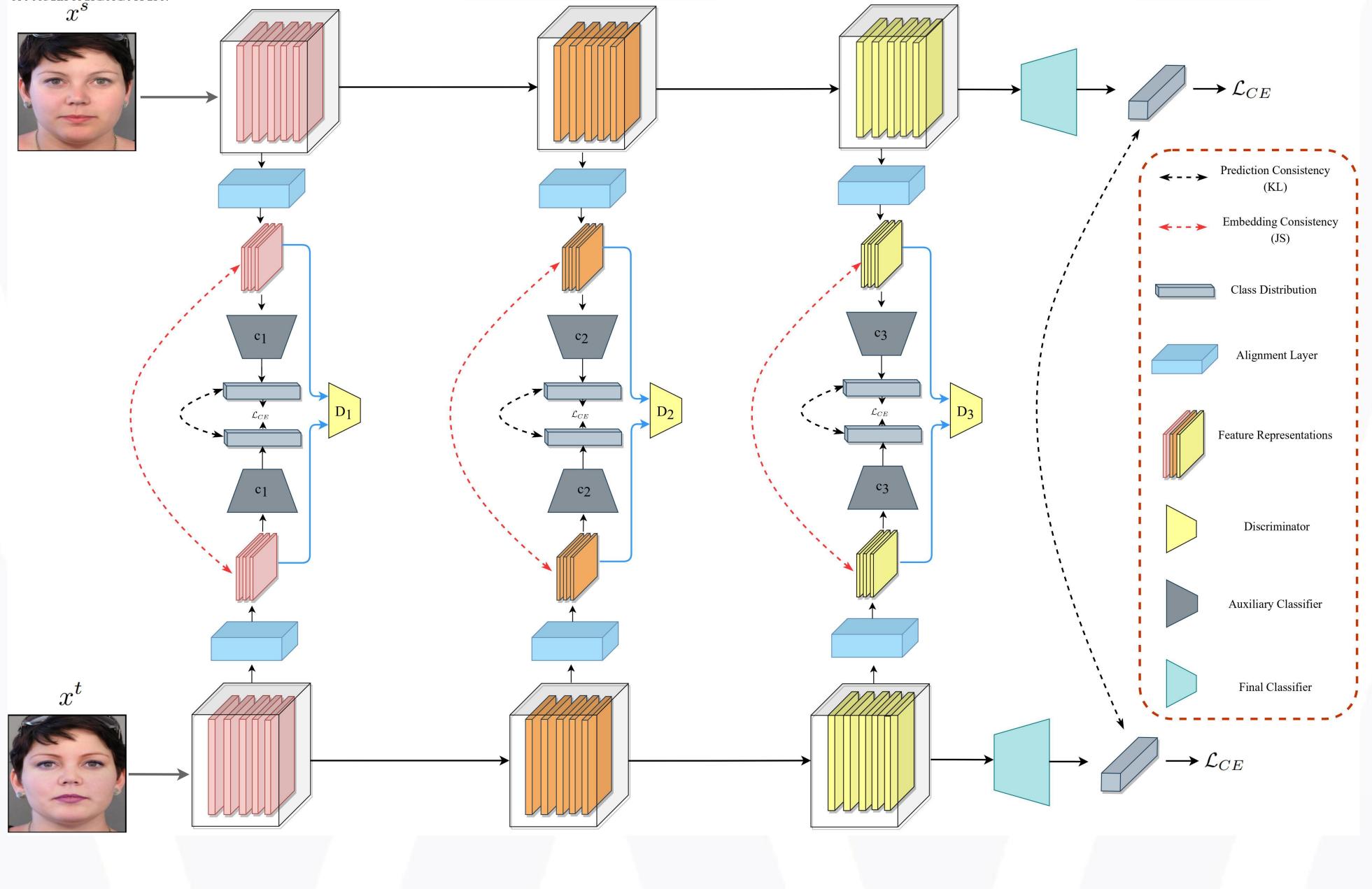
Face morphing is an image manipulation where two faces are blended together. At the time of passport enrollment, the passport photo can be easily manipulated with a morphing attack without the requirement of advanced forgery.

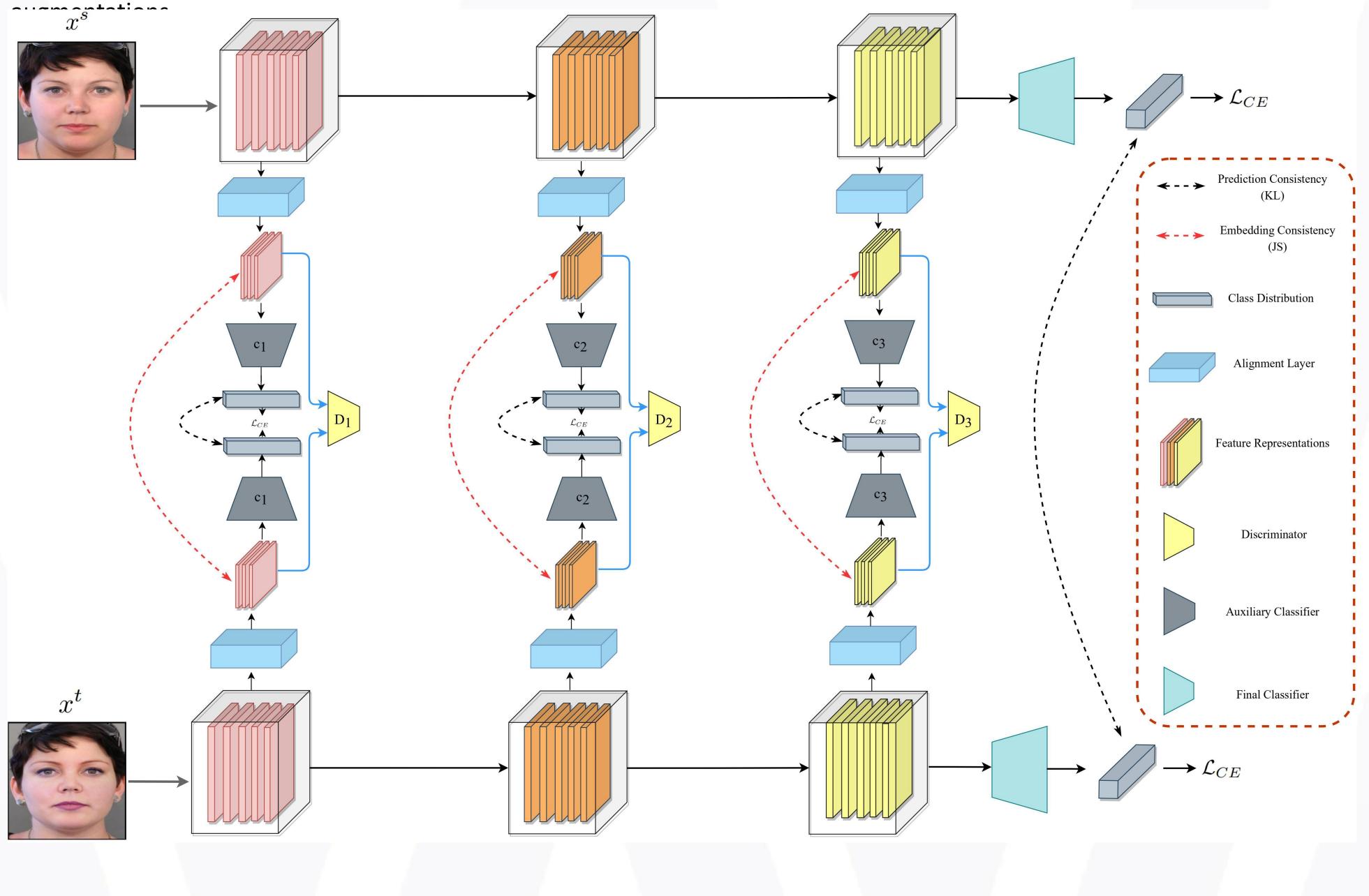


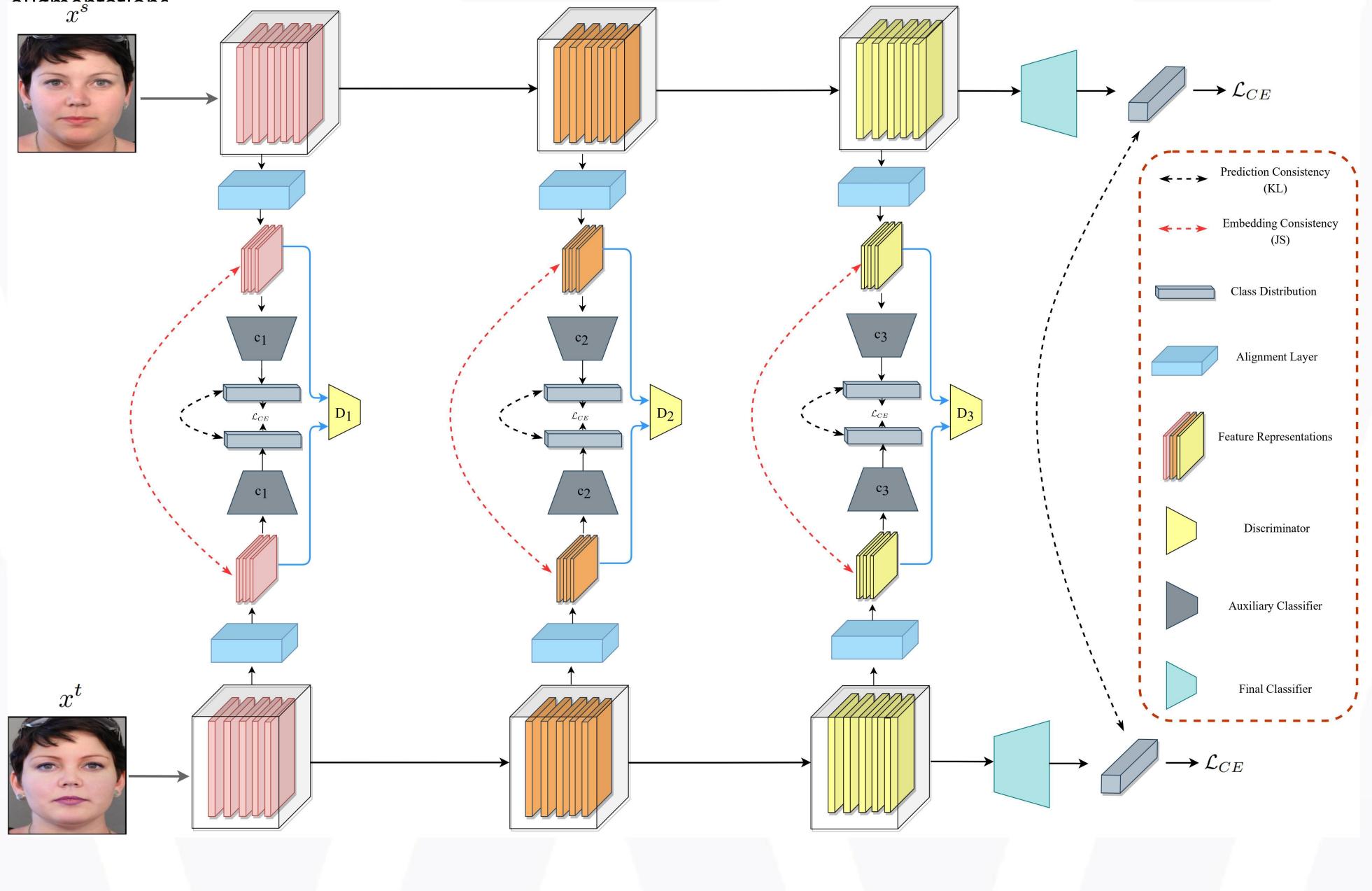


Proposed Method

- To improve a generalized morph attack detection, we impose consistency regularization at both the logit and feature representation levels using Kullback–Leibler (KL) divergence minimization. For this objective, several regularization branches are first integrated into the intermediate layers of our model and the embedding levels are computed at these branches.
- To learn the domain-shared feature representation, we employ adversarial feature learning at different feature \bullet representation levels. A feature extractor competes with a domain discriminator to learn a domain-shared feature representation and the domain discriminator determines whether the input images come from the intact morph images or the augmented ones.
- To explore a wide space of realistic morph transformations in our consistency regularization, we propose the ISM and the SM \bullet







Motivation

• We can enhance the generalization capability of morph attack detection from the perspective of consistency regularization.

 Consistency regularization operates under the premise that generalizable morph attack detection should output consistent predictions irrespective of the possible variations that may occur in the input space.

Contribution

• We regularize morph attack detection model to predict consistent results regardless of potential variations caused by diverse morph attacks, image quality, and environmental situations.

• We propose two morph-wise augmentations to explore a wide space of realistic morph attack transformations in our consistency regularization.

• We carry out extensive evaluations on several datasets to validate the generalization capability of our morph attack detection.

Challenges

There exist large domain shifts between different morph attacks.



New Augmentation

We propose the Inter-domain Style Mixup (ISM) augmentation, which employs the photo-realistic style transfer to synthesizes unseen morph attacks with new styles, while keeping the content of the input morph images unchanged.



Evaluations

• In the cross-morph evaluations, we use the FRGC FaceMorpher the training data and the test sets belongs to the FRGC morph faces with StyleGAN2, MIPGAN, and OpenCV morphing attacks. Our method is denoted by GRL. As reported in Table 1, the proposed GRL outperforms its competitors in all comparisons.

> Table 1. Cross-morph evaluations of the proposed method with the state-of-the-art studies on FRGC datasets. The results are in terms of APCER1 (@BPCER=1%), APCER5 (@BPCER=5%), APCER (@BPCER10=10%), EER, and AUC metrics.

	Method	APCER1%	APCER5%	APCER10%	EER	AUC
MIPGAN	ConvNext	17.40	3.07	1.20	16.33	99.17
	Inception	61.98	36.68	23.82	17.26	91.12
	Residual	-	-	-	6.67	-
	GRL	00.00	00.00	00.00	4.28	99.99
StyleGAN	ConvNext	44.60	14.52	2.80	7.65	97.57
	Inception	50.60	32.39	25.56	17.26	94.89
	GRL	00.00	00.00	00.00	00.00	100.00
OpenCV	ConvNext	60.68	29.66	12.65	11.50	95.27
	Inception	00.00	00.00	00.00	00.00	100.00
	GRL	00.00	00.00	00.00	00.00	100.00

• In the cross-domain evaluations, we use Twins morph dataset as the training set and the test sets belongs to the FRGC, AMSL, FERET, VISAPP17, and FRLL datasets

Conclusion

• Our paper introduces a morph attack detection system with strong generalization capabilities across various morph attacks, as demonstrated in experiments on multiple datasets..

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Acknowledgment

In addition, we propose the Self-morphing (SM) augmentation to synthesize morph attacks with minimal visual artifacts using several instances of the same identity.



with landmark-based and GAN-based morphing attacks. These attacks consists of StyleGAN2, WebMorph, OpenCV, and FaceMorpher attacks. As reported in Table 2, the proposed GRL outperforms its competitors in all annaricana

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Table 2. Cross-domain comparison of the proposed GRL with the state-of-the-art studies. The evaluations are in terms of the EER metric.

Methods	ALL AND	We fill the	A Charles	Screech	Face ADL	Perfect V	Style GAN	Face Norther	AC CO	School of the of	Ascent OC	CO C	Cloop Str	Chr. Al
SPL-MAD	12.09	15.72	5.78	12.92	4.67	30.21	28.95	25.76	19.54	15.57	18.42	-		29.54
MixFacenet	15.18	12.35	4.39	8.99	3.87	-	-	-	-	-	-	-		23.72
Inception	10.79	9.86	5.38	11.37	3.17	-	-	-	-	-	-	-		19.01
PW-MAD	15.18	16.65	2.42	16.64	2.20	-	-	-	-	-	-	-		20.39
Hamza	-	-	-	-	-	13.5	-	11.5	-	-	-	-	-	-
D Quality	7.91	7.13	5.41	7.04	3.60	12.29	13.99	10.80	24.48	14.32	24.17	-		25.09
OrthoMAD	14.80	15.23	0.73	6.54	0.98	-	-	-	-	-	-	-	-	-
Residuals (LMA)	-	-	-	-	-	-	-	-	-	0.17	-	13.92	-	-
Mutual	3.11	-	-	-	-	-	-	-	-	-	-	-	4.69	-
Scale-Space Gradients	-	-	-	-	-	-	-	0.98	-	-	-	6.67	-	