A. Generalization of DEUA on Diverse Generative Models

Although DEUA is primarily designed for diffusion-based detection and is orthogonal to many unified detection methods, it remains highly competitive with state-of-the-art unified detectors and can serve as a robust component within broader detection frameworks. To comprehensively assess its generalization ability, we further evaluated DEUA on the *UniversalFakeDetect* dataset, which encompasses a diverse set of generative models, including both diffusion and non-diffusion architectures. Under the SDv1.4 setting and leveraging only publicly available pretrained models or code, DEUA achieved competitive or even superior performance compared to existing unified detectors when trained on diffusion models (Tab. 5). These results demonstrate that DEUA not only excels in its targeted domain but also exhibits strong generalizability across a wide spectrum of generative models.

Furthermore, we investigated the robustness of DEUA on novel generative paradigms, such as diffusion transformers and autoregressive models, which represent the latest advancements in image synthesis. As shown in Tab. 6, DEUA consistently maintains high detection accuracy on these emerging architectures, further confirming its adaptability and effectiveness. These findings suggest that, despite being tailored for diffusion-based detection, DEUA possesses the flexibility to handle a broad range of generative models, making it a promising candidate for integration into future unified deepfake detection systems.

Method	Unet	Transformer		Autoregressive	Avg.
	SDv1.4	SDv3	SDv3.5	JanusPRO	
NPR (ProGAN)	76.6	76.2	77.8	76.3	76.7
FatFormer (ProGAN)	83.2	70.1	65.4	82.6	75.3
NPR (SDv1.4)	98.2	80.1	83.6	86.5	87.1
DRCT (SDv1.4)	95.1	91.2	90.4	93.9	92.7
DEUA (SDv1.4)	99.2	97.3	96.1	98.1	97.7

Table 6. ACC comparison on new generators. SDv3, sdv3.5 and JanusPRO are collected following GenImage. Results of NPR, FatFormer and DRCT are obtained using their official checkpoints.

Method	GAN						Deep fakes	Low level		Perceptual loss		Guided	LDM			Glide			Dalle	Avg.
	Pro-GAN	Cycle-GAN	Big-GAN	Style-GAN	Gau-GAN	Star-GAN		SITD	SAN	CRN	IMLE		200 steps	200 w/cfg	100 steps	100 27	50 27	100 10		
NPR (ProGAN)	99.8	95.0	87.6	96.2	86.6	99.8	76.9	66.9	98.6	50.0	50.0	84.6	97.7	98.0	98.2	96.3	97.2	97.4	87.2	87.6
FatFormer (ProGAN)	99.9	99.3	99.5	97.2	99.4	99.8	93.2	81.1	68.0	69.5	69.5	76.0	98.6	94.9	98.7	94.4	94.7	94.2	98.8	90.9
NPR (SDv1.4)	57.2	73.8	65.2	66.0	53.5	99.0	52.9	53.0	68.4	48.8	50.8	56.2	92.6	92.9	92.7	90.8	86.4	89.9	69.5	71.6
DRCT (SDv1.4)	99.6	93.6	87.6	99.2	90.1	99.9	72.3	67.8	60.5	68.2	59.3	92.9	99.8	99.6	99.8	99.8	99.8	99.9	91.2	88.5
DEUA (SDv1.4)	99.5	94.2	85.3	98.4	90.5	99.5	80.6	72.5	76.4	71.3	74.5	94.8	99.5	99.6	99.9	99.6	99.8	99.8	96.4	91.2

Table 5. ACC comparisons on the UniversalFakeDetect Dataset. Results of NPR, FatFormer and C2P-CLIP trained on ProGAN are from paper C2P-CLIP. Results of NPR and DRCT trained on GenImage SDv1.4 are obtained using their official checkpoints.