ETRA Privacy and Ethics Statement

In this paper, the authors proposed the use of iris style feature for iris recognition, and the use of neural style transfer to mask identifiable iris style features. The former is proved to be most robust against image rotation and perspective transform, which can enhance iris-based authentication and identification, while the latter can be used to secure iris-based biometrics. The authors have also shown that the risk of misuse of iris style transfer for malicious purposes, such as faking one's presence, is relative low compared to previous works.

A Implementation

We published our code on https://github.com/AnonymWriter/Iris-Style-Transfer for reproducibility. The repository is anonymized for review.

B Randomness

To guarantee reproducibility, we fixed random seed to 42 at the very beginning of our program. The random seed was fed to *numpy.random.seed*, *torch.manual_seed*, and *random.seed*.

C Dataset

The OpenEDS2019 [Garbin et al. 2019] dataset contains four parts, namely: segmentation data, generative data, sequence data, and corneal topography data. We considered only the segmentation data, whose details are given in Table 3.

Property	**OpenEDS2019 (segmentation)**
samples	12,759
users	152
modality	grayscale image
resolution	640×400
ground truth	segmentation labels

Table 3. Experiment environment.

D Environment

Our environment by date November 1st, 2024 was listed in Table 4. It should be noticed that although our code can be run on a device without dedicated GPU, it is recommended to run the program on a computer with ≥ 32GB RAM and a dGPU with ≥ 32GB VRAM.

Hardware	**Specification**
CPU	AMD EPYC 7763 64-Core
GPU	NVIDIA A100 80GB PCIe×4
Memory	1TB

Software	**Version**
OS	Ubuntu 22.04.4 LTS
Python	3.12.4 by Anaconda
PyTorch	2.4.1 for CUDA 12.4
Scikit-Learn	1.4.2
WandB	0.18.5

Table 4. Experiment environment.

E Hyperparameters

For training the classifiers, we used the Adam optimizer and conducted grid search in range $\{1e-6, 1e-5, 1e-4, 1e-3, 1e-2\}$ for optimal learning rates. The best performing learning rates were $1e-5$ for both feature sets. For style transfer, we followed the instruction given by [Gatys 2017], namely using an LBFGS optimize with learning 1.0. Throughout the experiments, we used a batch size of 64. The hyperparameters were listed in Table 5 for a clear view.

Hyperparameter	Value
optimizer (classifiers)	Adam
optimizer (style transfer)	LBFGS
learning rate (classifiers)	$1e-5$
learning rate (style transfer)	1.0
batch size	64
image scaling	224×224

Table 5. Details of hyperparameters.

F Model Structures

We implemented two different projection heads. The first one was designed for conventional VGG features, whereas the second was tailor for style features. We designed the structures of both heads so that they resemble the original VGG projection head as much as possible. The architectures of them are given in Tables 6 and 7:

Layer	Specification
AdaptiveAvgPoll2d	output_size = (7, 7)
Flatten	-
Linear	in = 25,088, out = 4.096, bias = True
ReLU	inplace = True
Dropout	p = 0.5, inplace = True
Linear	in = 4,096, out = 4,096, bias = True
ReLU	inplace = True
Dropout	p = 0.5, inplace = True
Linear	in = 4,096, out = 151, bias = True

Table 6. Structure of projection head (VGG feature).

Layer	Specification
Linear	in = 1,920 , out = 4.096, bias = True
ReLU	inplace = True
Dropout	p = 0.5, inplace = True
Linear	in = 4,096, out = 4,096, bias = True
ReLU	inplace = True
Dropout	p = 0.5, inplace = True
Linear	in = 4,096, out = 151, bias = True

Table 7. Structure of projection head (style feature).

G Additional Results

Additional results measured with F1 score and Matthews correlation coefficient (MCC) were given here.

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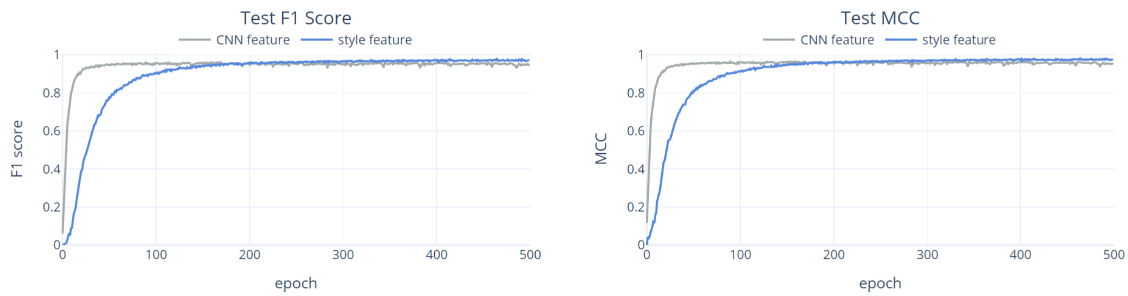

Fig. 9. Test performance of style feature and common CNN feature for iris recognition.

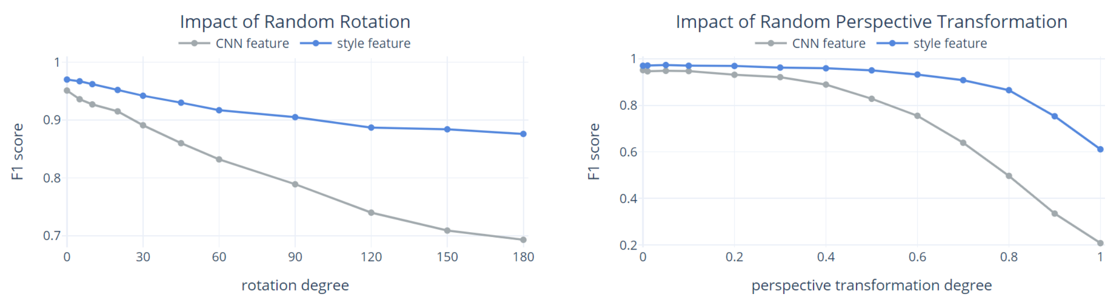

Fig. 10. Style feature vs. common CNN feature regarding robustness against random rotation and perspective transformation (F1 score).

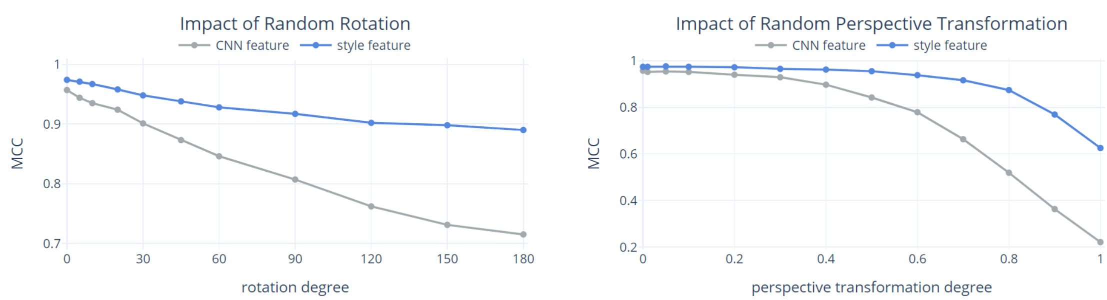

Fig. 11. Style feature vs. common CNN feature regarding robustness against random rotation and perspective transformation (MCC).