Microsoft

CVPR

微软亚洲研究院创研论坛

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Face X-Ray for More General Face Forgery Detection

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CVPR2020 Oral Presentation
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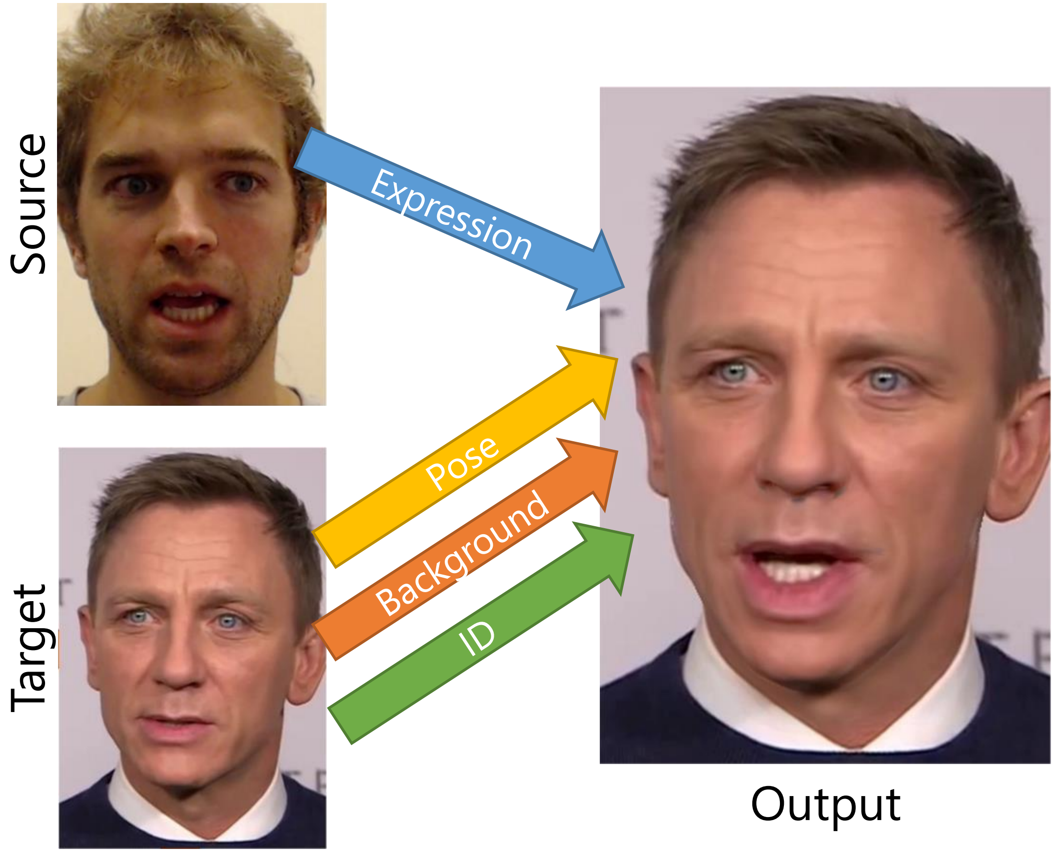
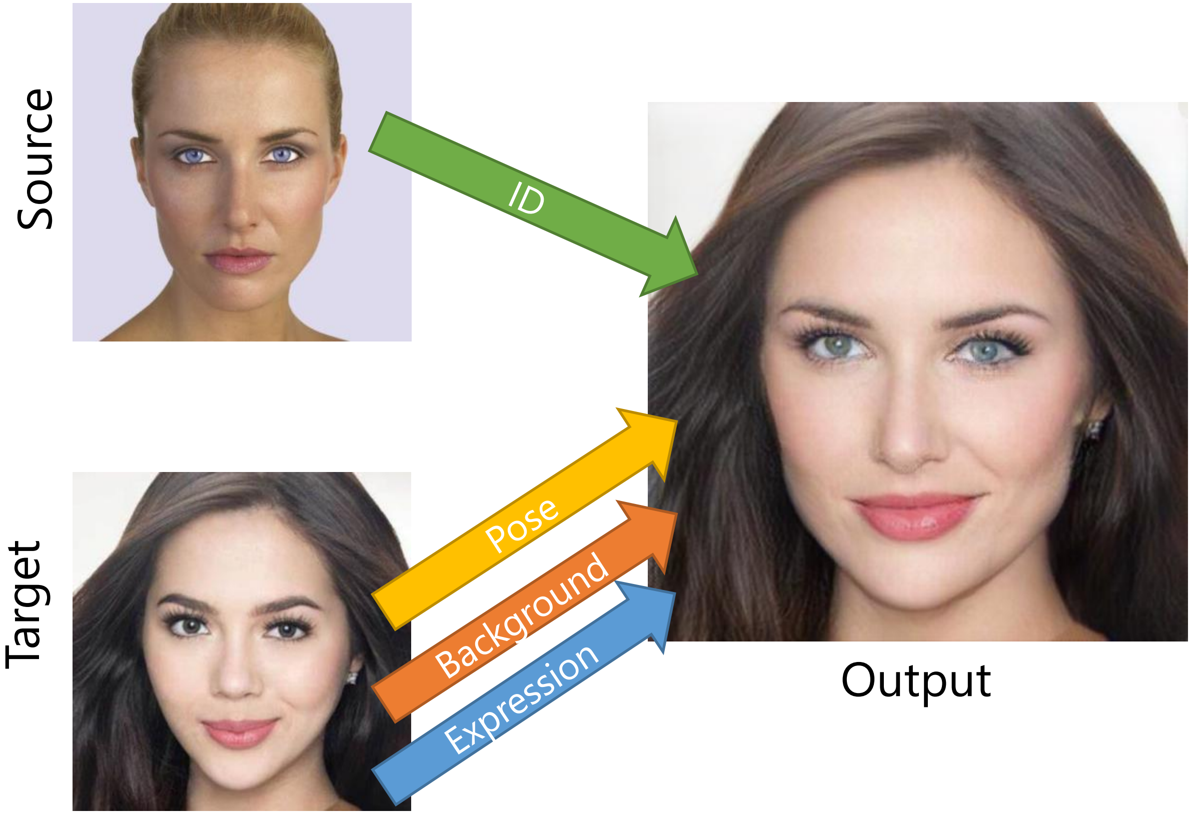
Face Forgery

Face Reenactment



Face Replacement



*Images of face reenactment are from paper "Face2Face: Real-time Face Capture and Reenactment of RGB Videos"

Deepfakes are eroding our trust

Source: Claire Wardle / New York Times

Fake videos appear real

Fake voices sound real

Thus, real media can't be trusted

Fake media production time	
10 years ago – by studios (CG + DSP)	Today – by anyone (AI/GANs + DSP)
Video: hundreds of hours Audio: dozens of hours	Video: hours Audio: minutes

Face manipulation detection dataset

- FaceForensics++ Datasets :
  - Real: 1000 videos downloaded from the Internet.
  - Fake: 1.5M images from 3000 videos containing 1000 identities.
  - Source: High quality videos, 70% training, 15% validation, 15% test.
  - Four Manipulation methods: DeepFake, FaceSwap, Face2Face, NeuralTexture.


Original
DeepFakes
Face2Face
FaceSwap

Manipulated Face Detection

- Human evaluation.
- Previous State-of-the-art: Binary classifiers for each kind of manipulation, backbone: XceptionNet.

AP	Deepfake	Face2Face	FaceSwap
Human*	77.22%	60.03%	77.25%
FaceForensics++*	98.76%	98.59%	98.53%

*The results are from paper: "Rössler, Andreas, et al. Faceforensics++: Learning to detect manipulated facial images, ICCV, 2019."

Has this problem been solved?

No!

Generalization Dilemma

- The naive baseline real/fake classifier failed to generalize to unknown face manipulation algorithms
- We present Face X-ray to tackle the generalization dilemma on unknown face manipulation algorithms

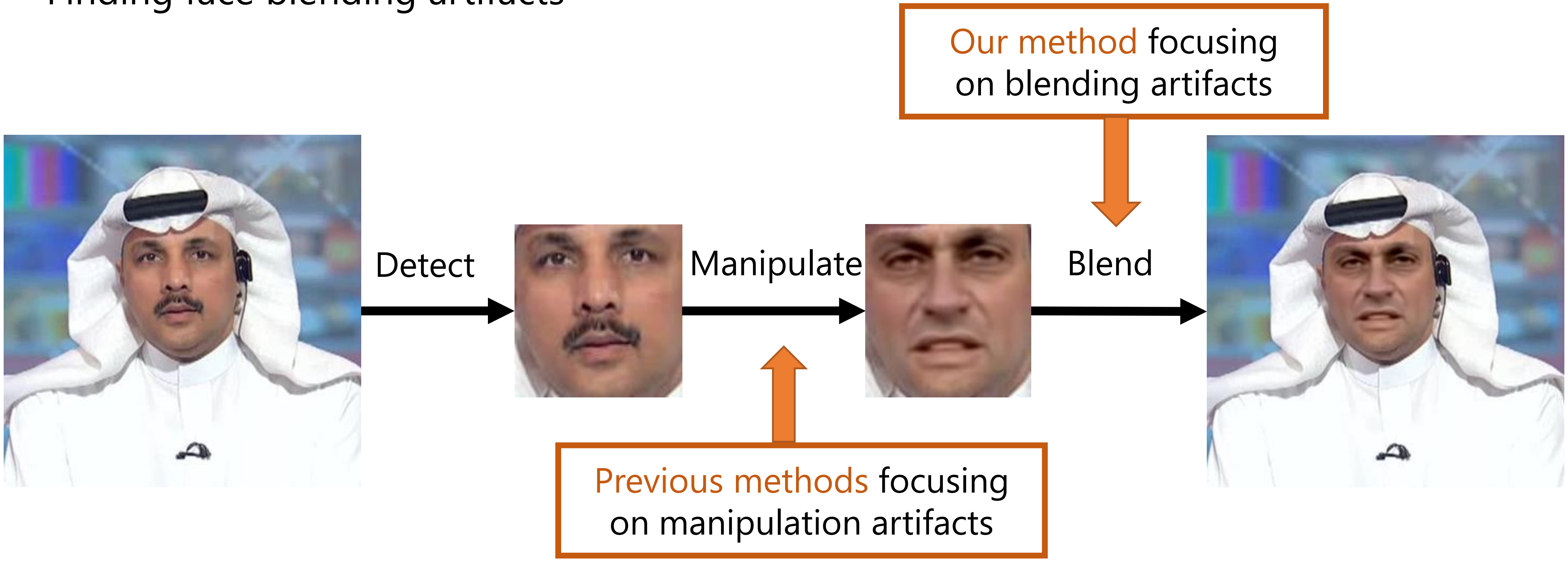
Training set			Binary classification (AP)		
Deepfake	Face2Face	FaceSwap	Deepfake	Face2Face	FaceSwap
√			99.13%	70.99%	51.12%
	√		82.25%	98.91%	63.82%
		√	65.40%	58.90%	99.20%

How we deal with the Generalization Dilemma?

Our idea: Looking for common defects

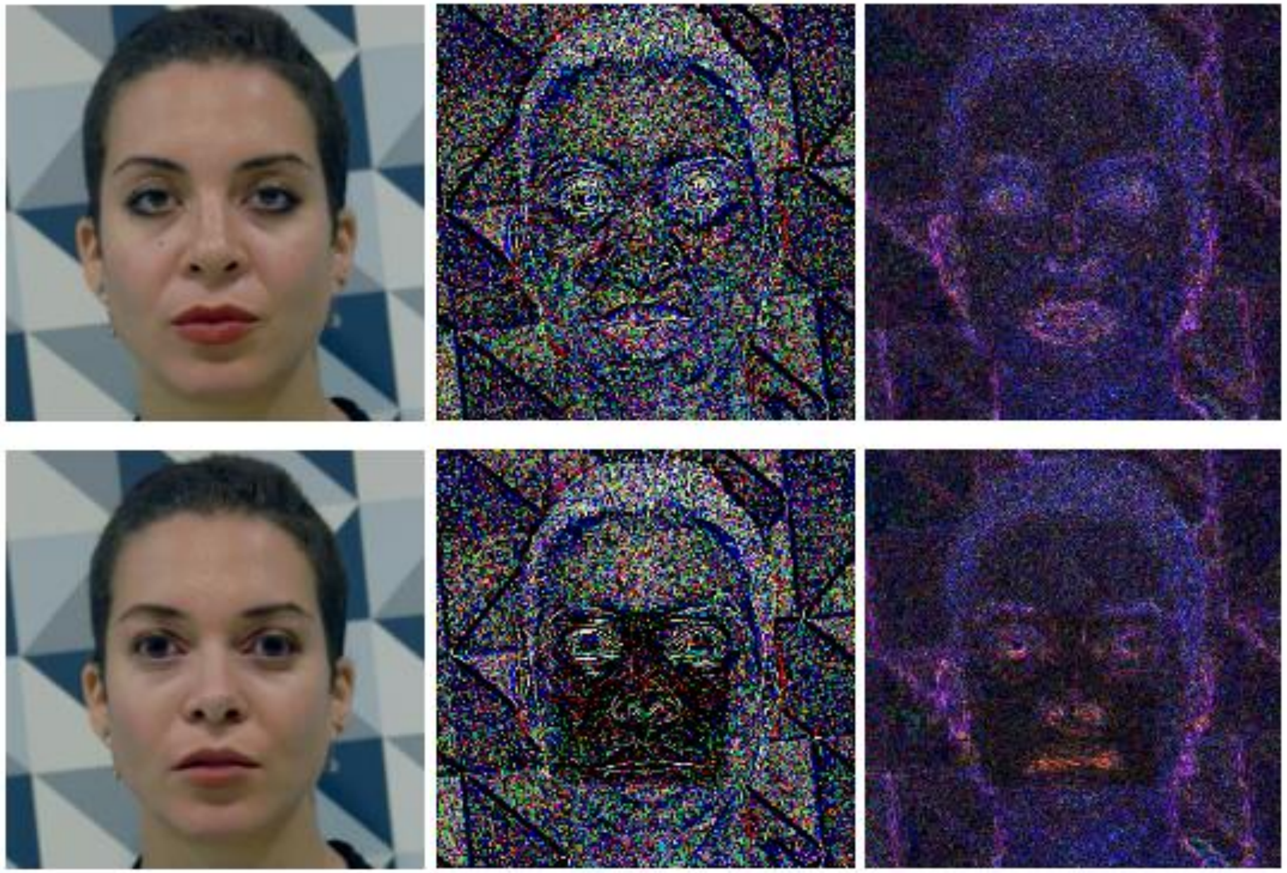
Our observation

- Face manipulation methods only generate inner face region
- Image blending exists in almost all face manipulation methods
- Finding face blending artifacts



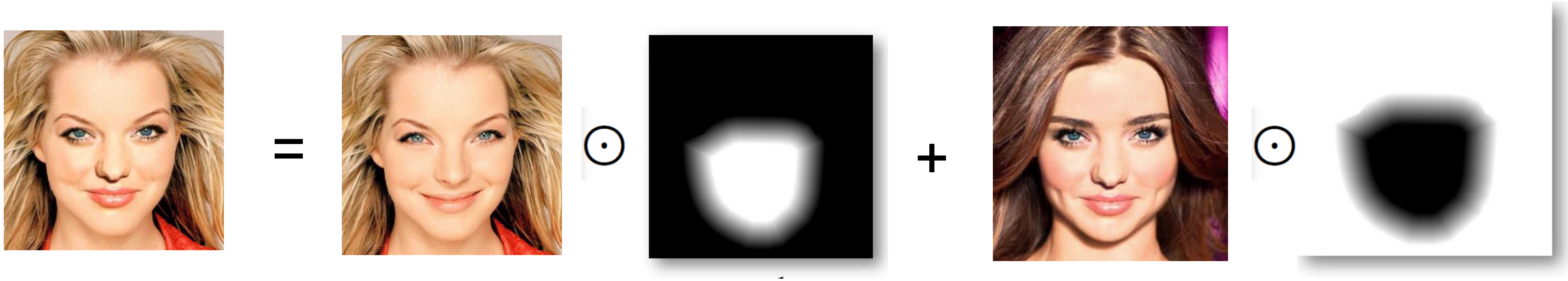
What is Blending Artifacts

- Each image has its own distinctive marks
- Introduced from hardware (e.g., sensor, lens) or software (e.g., compression, synthesis algorithm)
- There is the strong possibility that some marks change across the boundary.



Blending boundary definition

- A typical Blending Step



- We define blending boundary as $(1 - mask) \times mask \times 4$

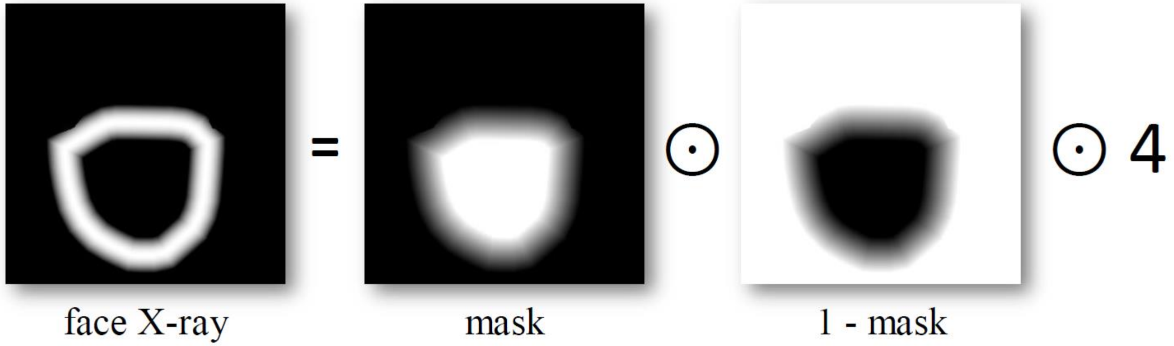
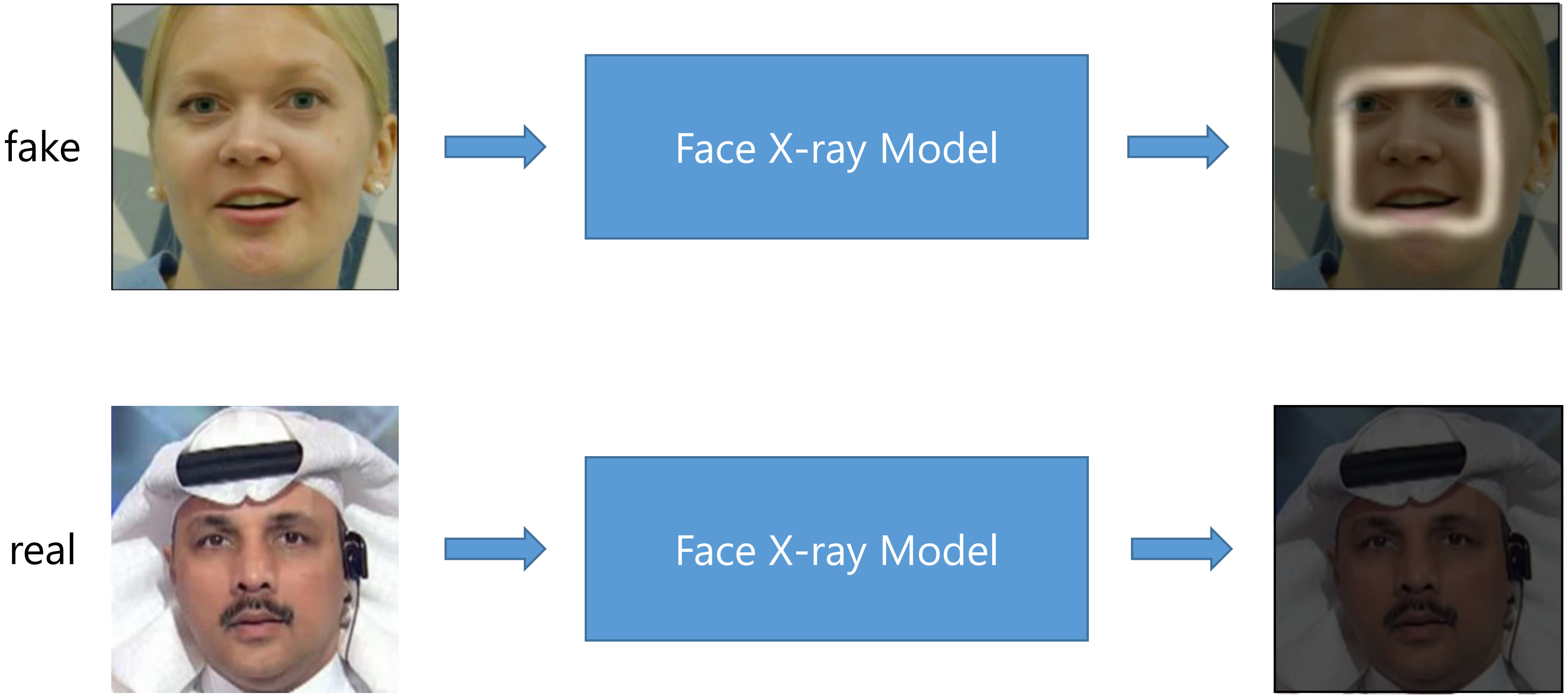


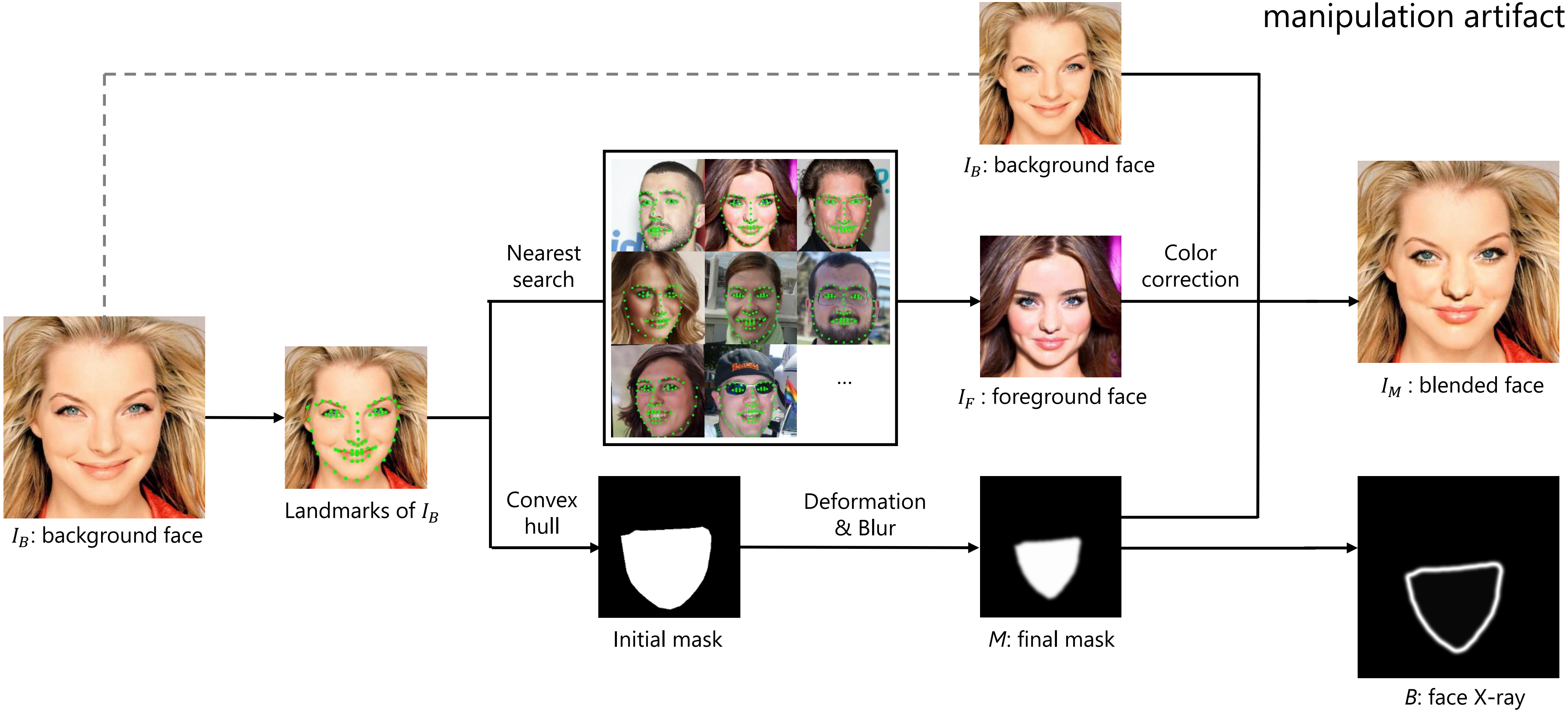
Illustration of our methods: Face X-ray

- Detecting blending boundary:

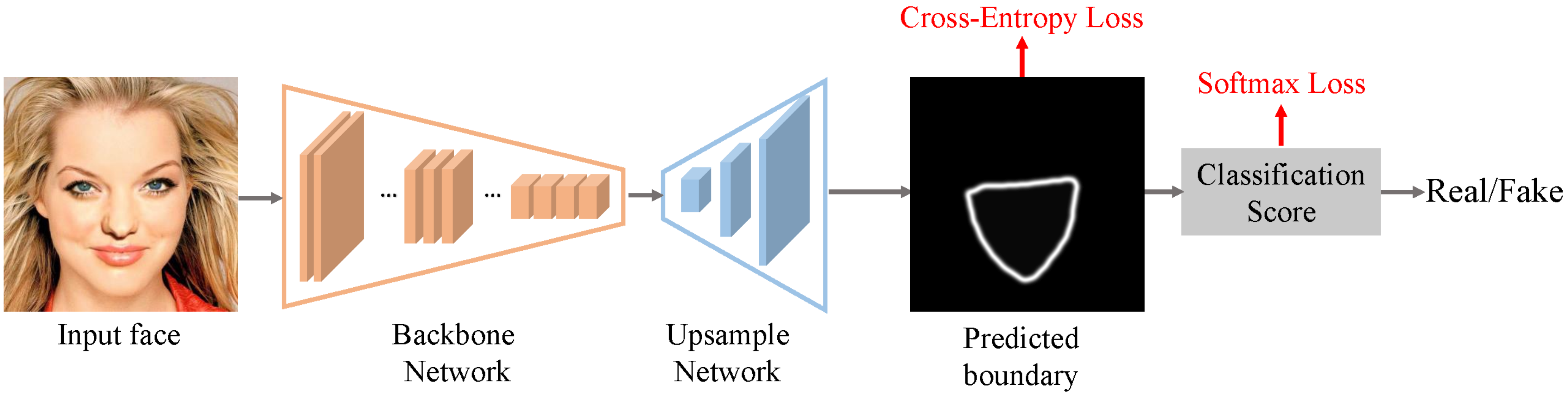


Training In A Self-Supervied Way

- Only utilize real images
- No other face manipulation data is required.
- Avoid falling into specific manipulation artifact



Our proposed framework



Experimental Results

Generalization Capability

- Training and testing with fake faces generated by different algorithms.

Model	Training set		Test set AUC				
	FS	BI	FS	DF	F2F	NT	ALL
Xception	√	-	99.36	87.56	61.70	68.71	74.91
HRNet	√	-	99.24	83.64	64.12	68.89	73.96
Face X-ray	√	-	99.20	98.52	92.29	86.63	93.13
	√	√	99.09	99.03	98.16	96.66	98.25
	-	√	99.21	99.17	**98.57**	**98.13**	**98.52**

Classification model has a terrible cross-algorithms generalization ability

Face X-ray can improve generalization performance significantly : △ **19.17**

Real-face based generated data further improve generalization performance : △ **5.12**

Comparable results with only the Blended image with real faces

Comparison with SOTA

- Our methods outperform SOTA methods by large margins.

	Training Set		**Detection accuracies**	
	F2F	FS	F2F	FS
LAE	√	-	90.93	63.15
FT-res	√	4 images	94.47	72.57
MTDS	√	-	92.77	54.07
Face X-ray	√	-	**97.73**	**85.69**

Ablation Study

- Training data(image and Face X-ray pair) generation with different settings.

	AUC	
	FF++	DFD
w/o mask deformation	93.92	85.89
w/o color correction	96.21	89.91
Face X-ray	**98.52**	**93.47**

Ablation Study

- Omethod remain effect to possion blending and a learning-based blending.

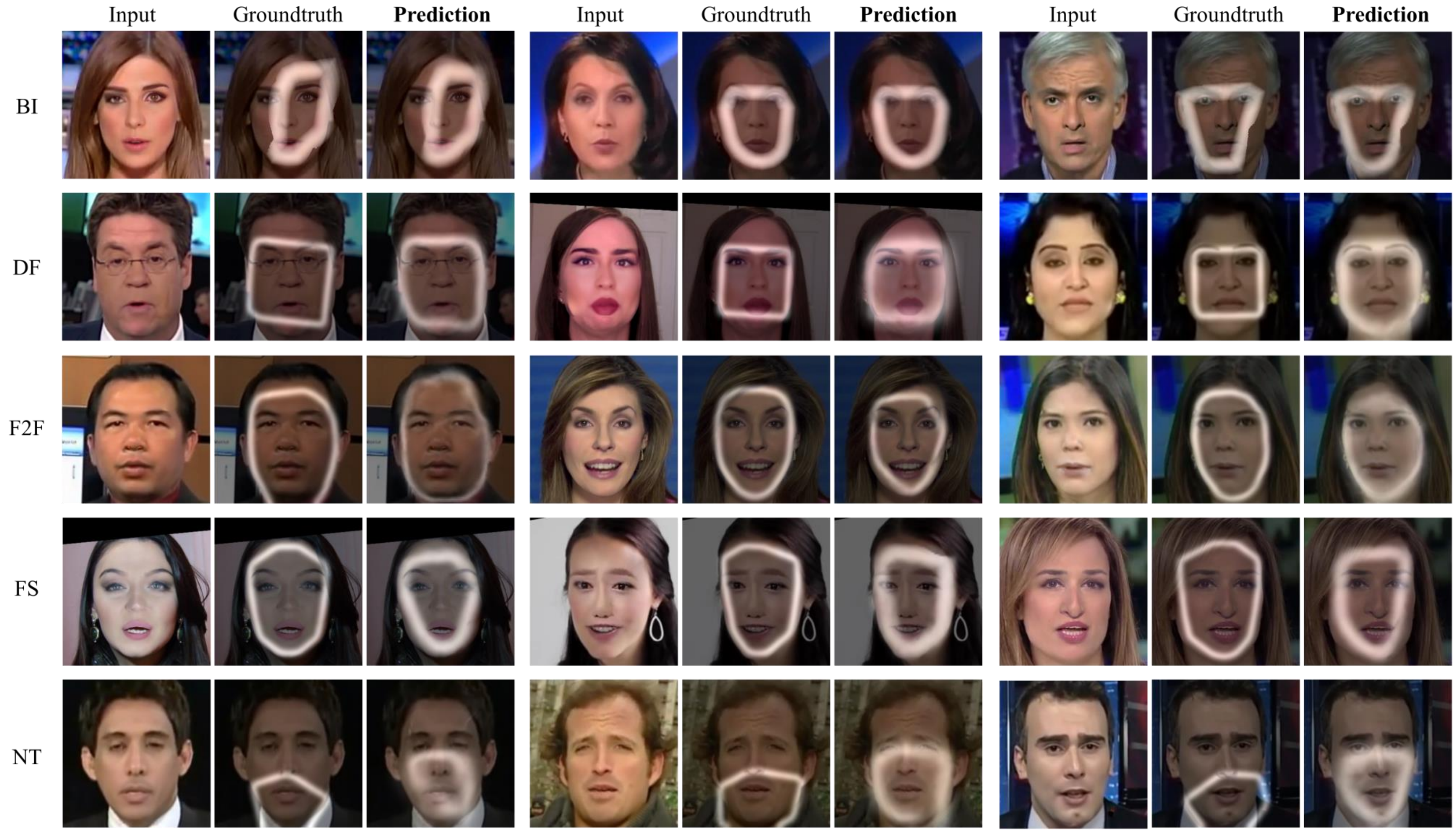
Blending type	AUC	AP	EER
Alpha blending	99.46	98.50	1.50
Possion blending	94.62	88.85	11.41
Deep Blending	99.90	98.77	1.36

Cross dataset results

- Training on FaceForensics++ dataset
- Testing on DFD, DFDC and Celeb-DF dataset

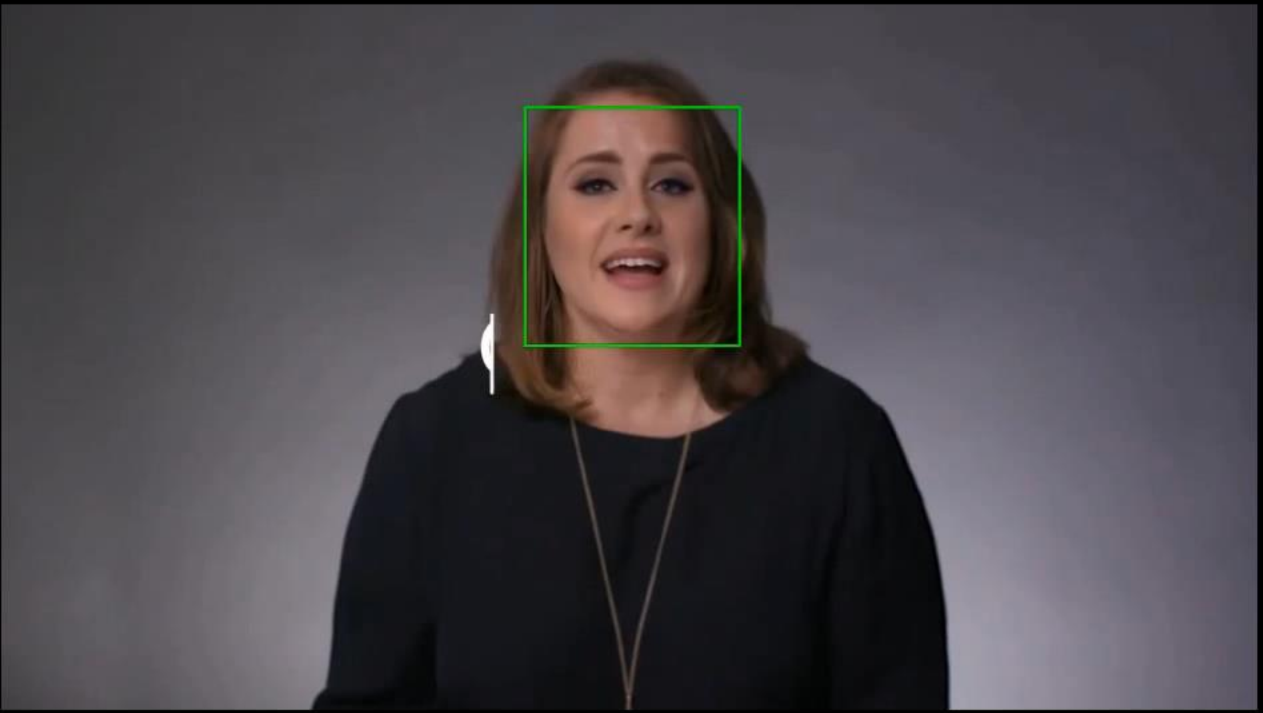
AP	DFD	DFDC	Celeb-DF
Binary classification	78.82%	50.83%	50.07%
Face X-ray	**93.34%**	**72.65%**	**73.33%**

Predicted blending boundary

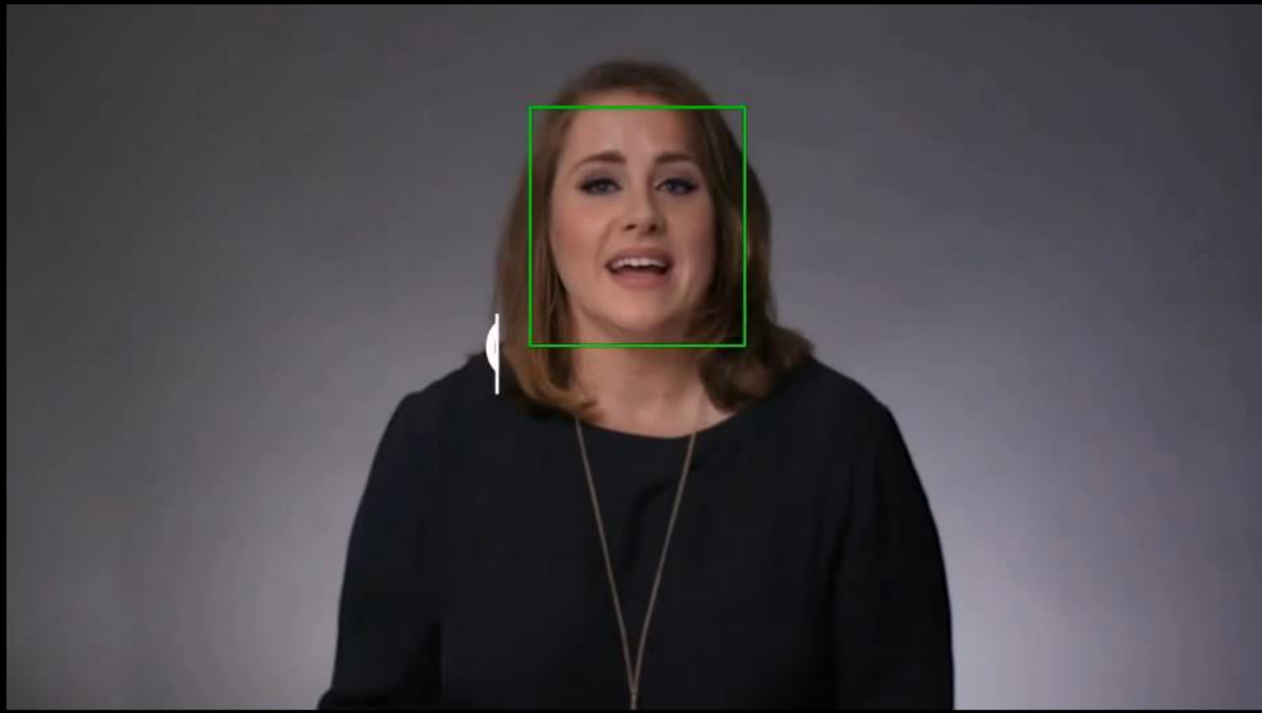


green box: real, red box: fake

FaceForensics++



Our predictions



Limitations

- Cat-mouse game
  - An image is entirely synthesis.
  - Adversarial samples to against our detector.
- Image/video compression
  - Suffer from performance drop when encounter low resolution Images.

AUC	No compression	Light compression	High compression
Face X-ray	98.52%	87.35%	61.6%

Conclusion

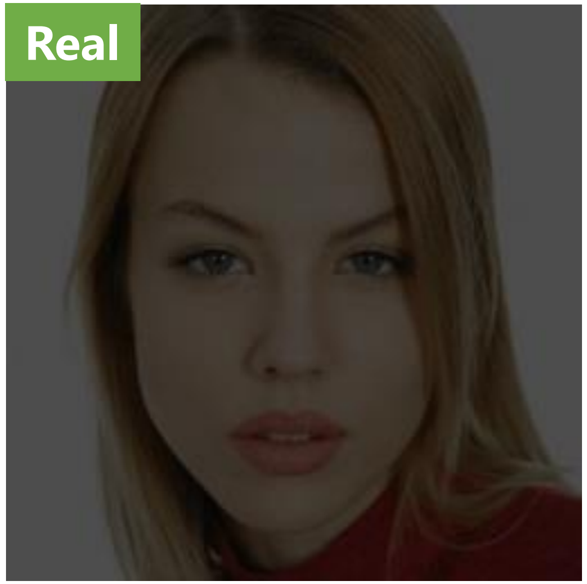
- Face X-ray: a novel framework for more general manipulated face detection.
- Our method not only distinguishes whether an image is forged but also identifies the location where two images are blending with each other.
- We train our framework in a self-supervised way that only utilize real images, making our model more robust and generalizable.

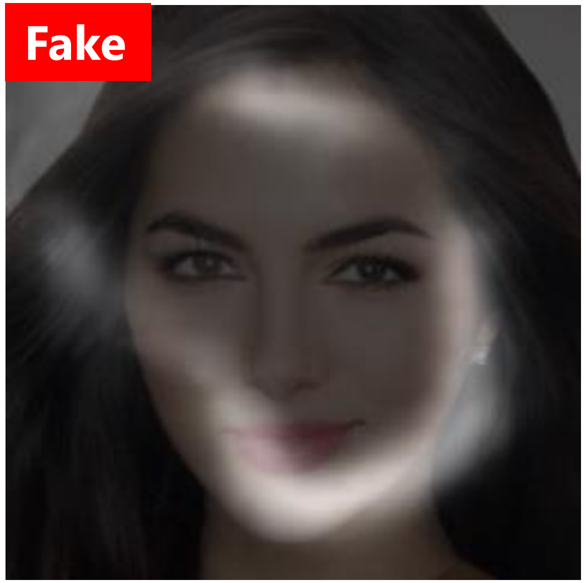
Real or Fake?




*Real images and source images are from https://www.bing.com. Fake Images are generated by our algorithm.

Real or Fake?





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谢谢观看

THANK YOU