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Recent Progress on Deepfake Detection

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3 FDJL: Forgery-Discomfort Joint Learning for Generalized Deepfake Detection

Background: Game




Real or Fake?

Background: Game

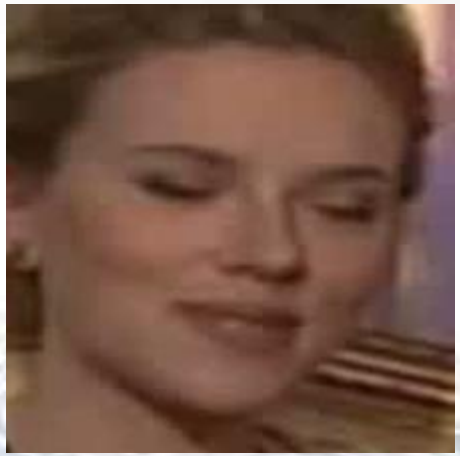
Fake

Fake

Fake

Fake

Real



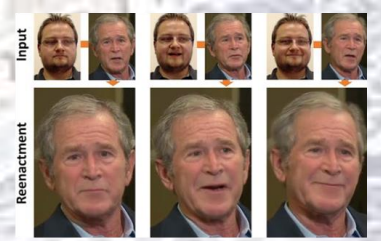
Real

Real

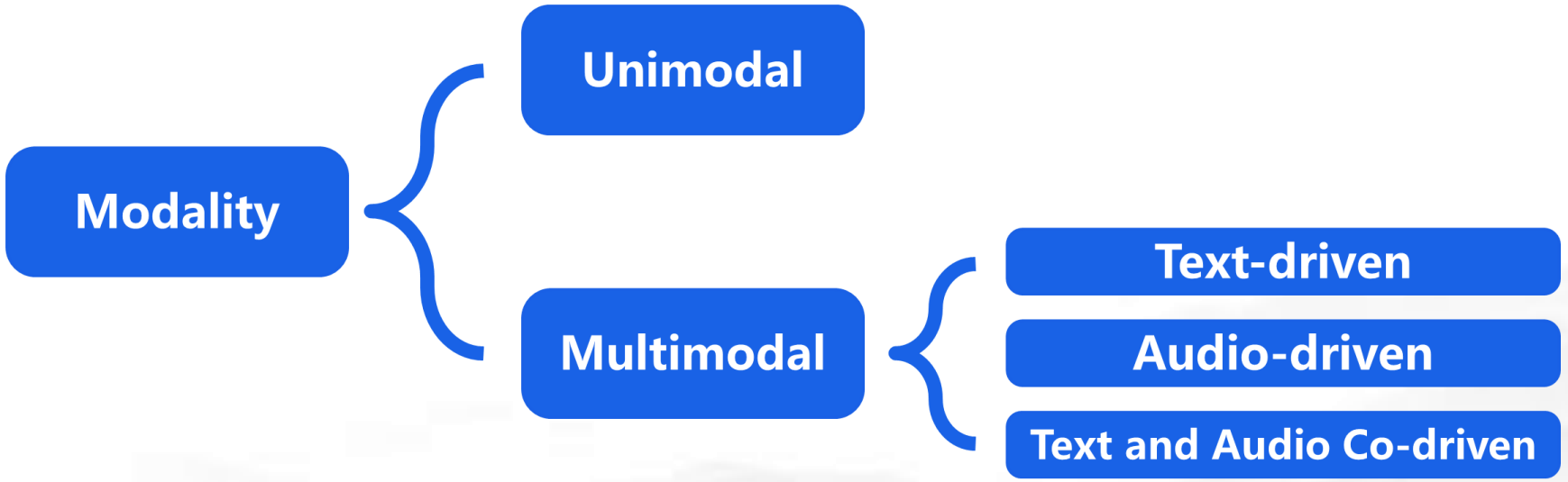
Real

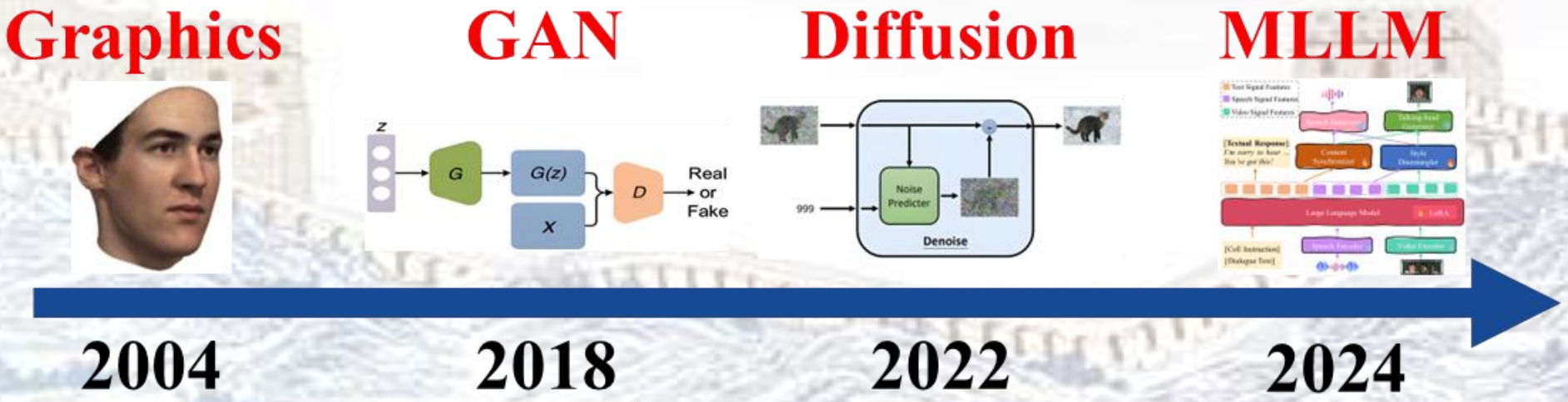
Background: Deepfake Generation

- **Deepfake Generation**
  - **Entire Face Synthesis**
    - Face Generation
    - Face Inpainting
    - Face Super-Resolution
  - **Face Swapping**
    - Face2Face
    - Face2Head
    - Expression Transfer
  - **Face Editing**
    - Attribute Editing
    - Expression Editing
    - Pose Editing
  - **Face Reenactment**
    - 2D Reenactment
    - 3D Reenactment
    - Audio Reenactment



Background: Deepfake Generation





Background: Threats and Solution

Explicit, AI-generated Taylor Swift images spread quickly on social media

By Samantha Murphy Kelly, CNN
4 min read · Published 3:19 PM EST, Thu January 25, 2024

Finance worker pays out $25 million after video call with deepfake ‘chief financial officer’

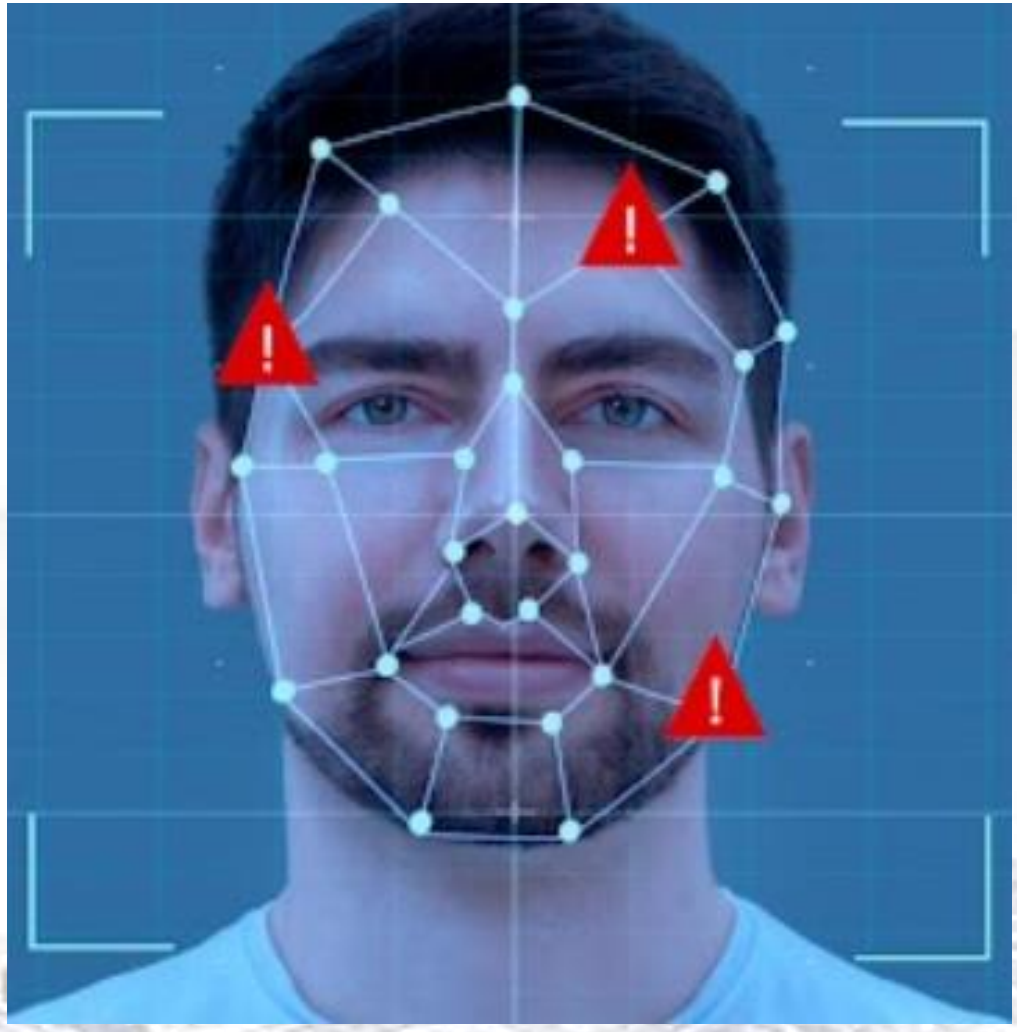
By Heather Chen and Kathleen Magramo, CNN
2 min read · Published 2:31 AM EST, Sun February 4, 2024

Deepfakes can cause long-lasting damage to children

Analysis by Kara Alaimo, CNN
5 min read · Updated 9:26 AM EST, Thu January 2, 2025

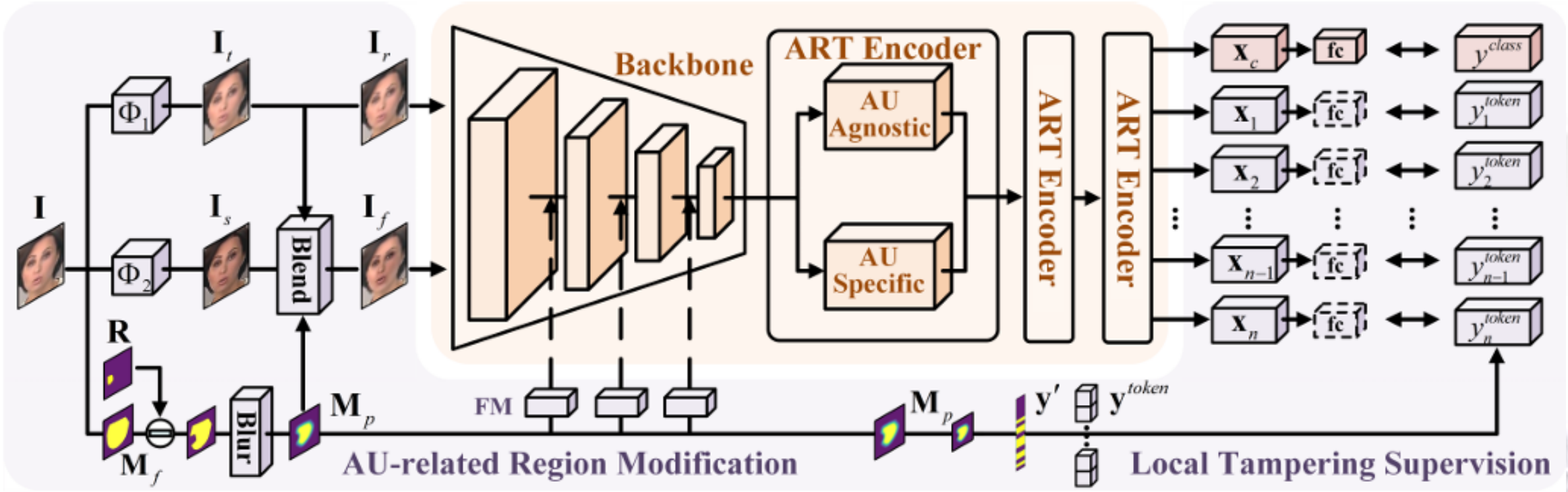
Victims of explicit deepfakes will now be able to take legal action against people who create them

By Clare Duffy, CNN
4 min read · Updated 10:29 PM EDT, Mon May 19, 2025



Problem: Forgery Feature Representation

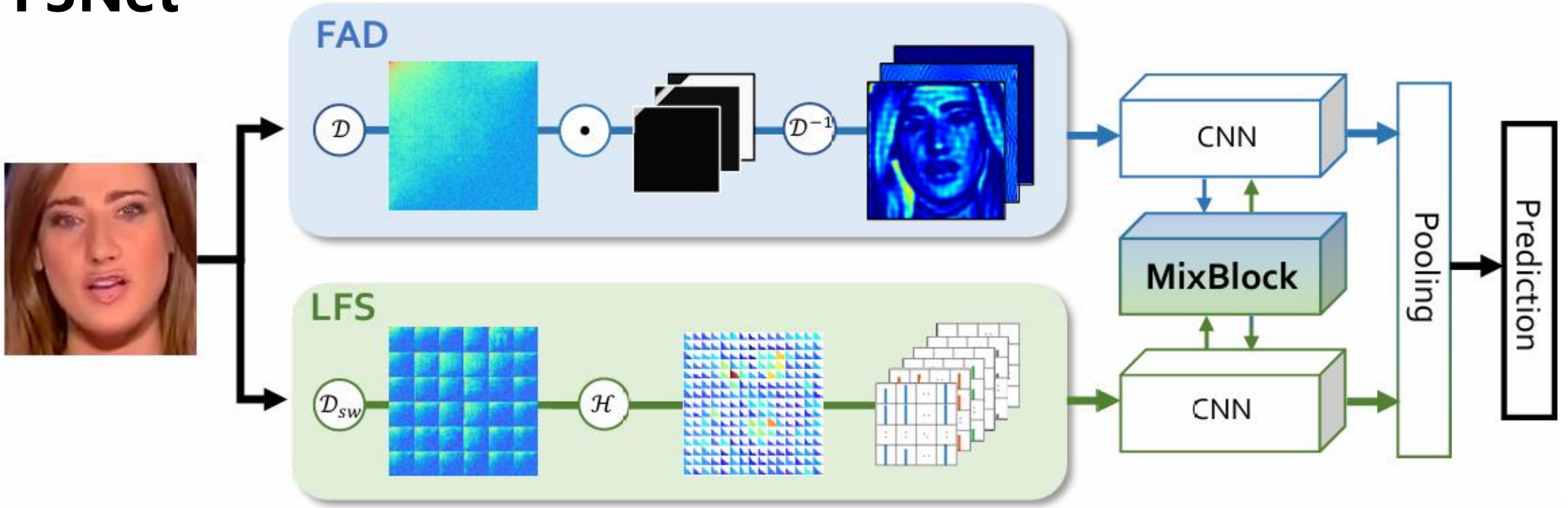
AUNet



Utilizing binary masks to represent forgery feature.

Problem: Forgery Feature Representation

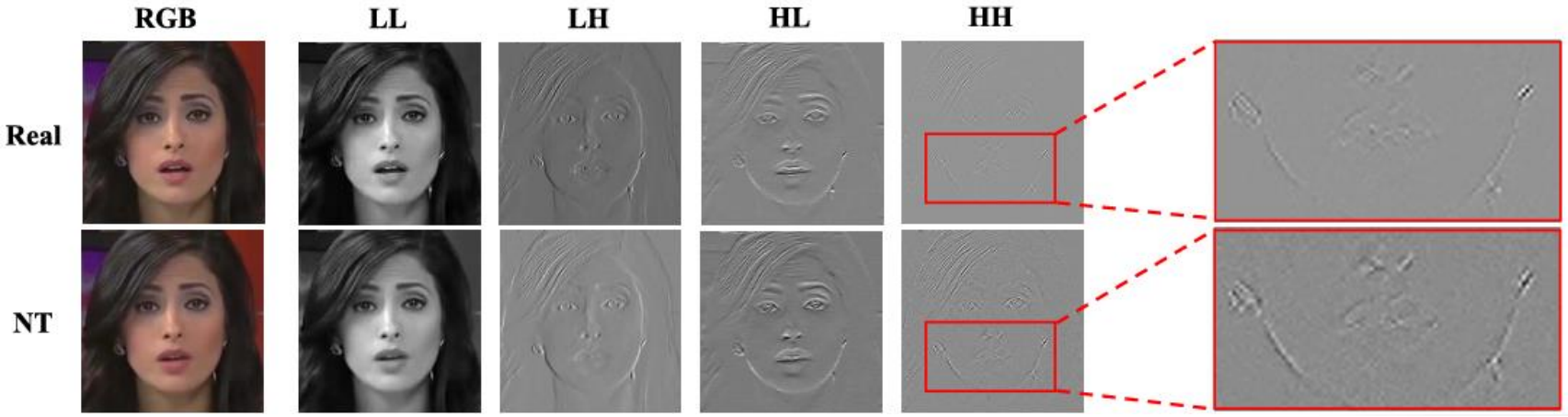
F3Net

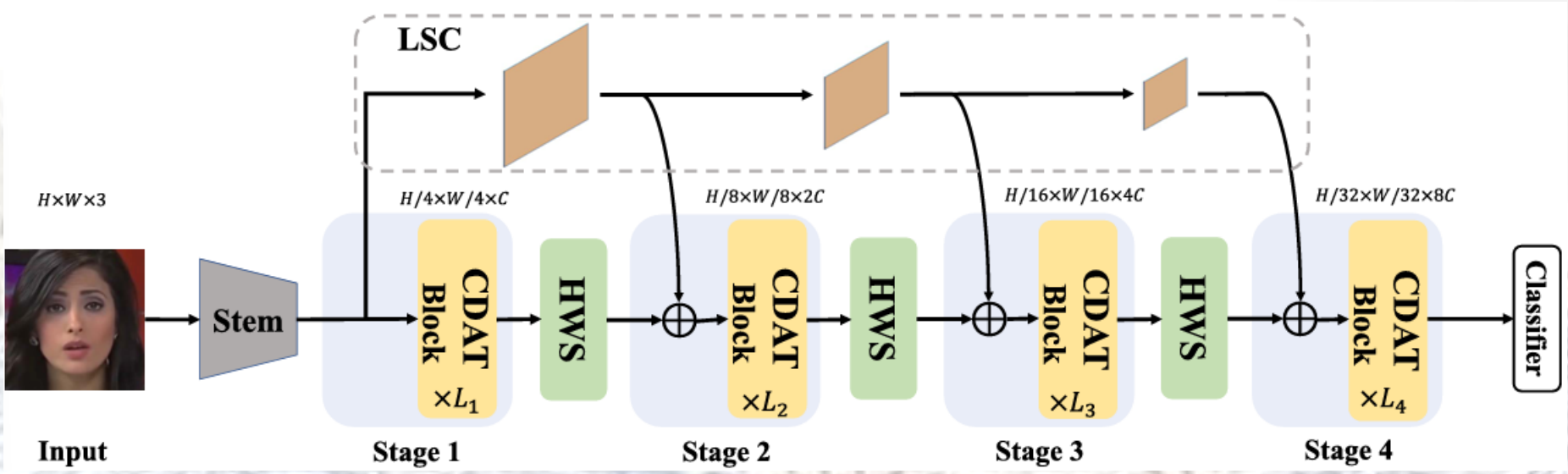


Utilizing Discrete Cosine Transform (DCT) and Local Frequency Statistics (LFS) for forgery feature representation.

Problem: Forgery Feature Representation

F2Trans





Utilizing wavelet transformation to represent forgery feature.

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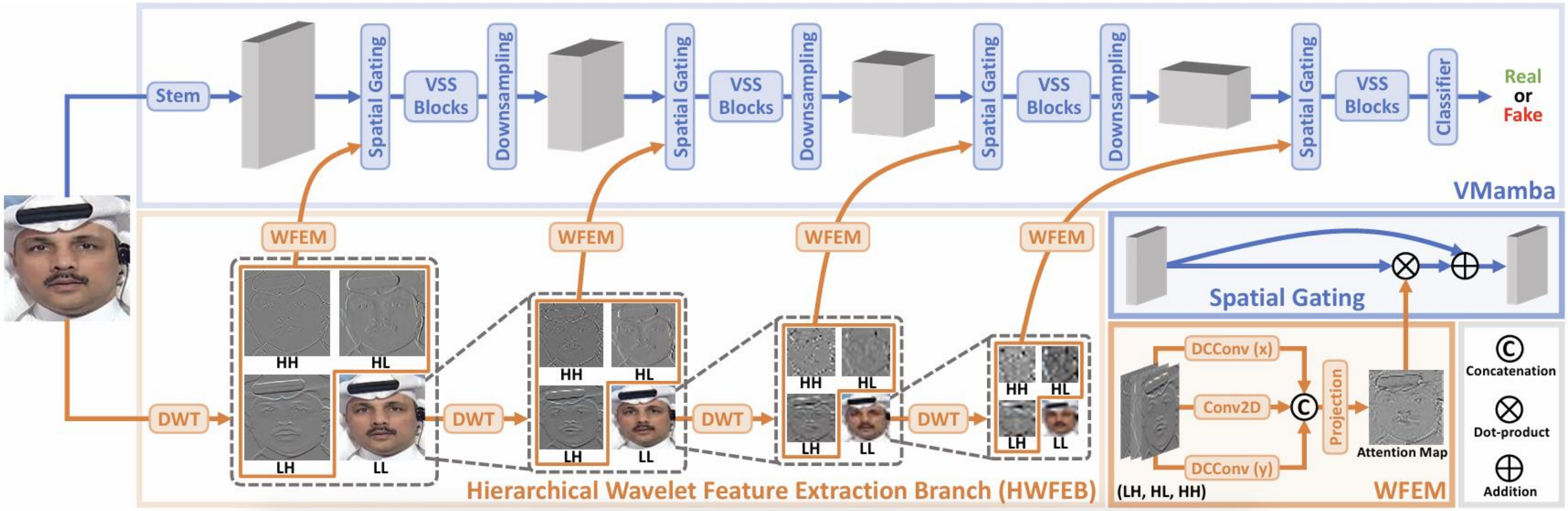
WMamba: Architecture



WMamba: Dynamic Contour Convolution

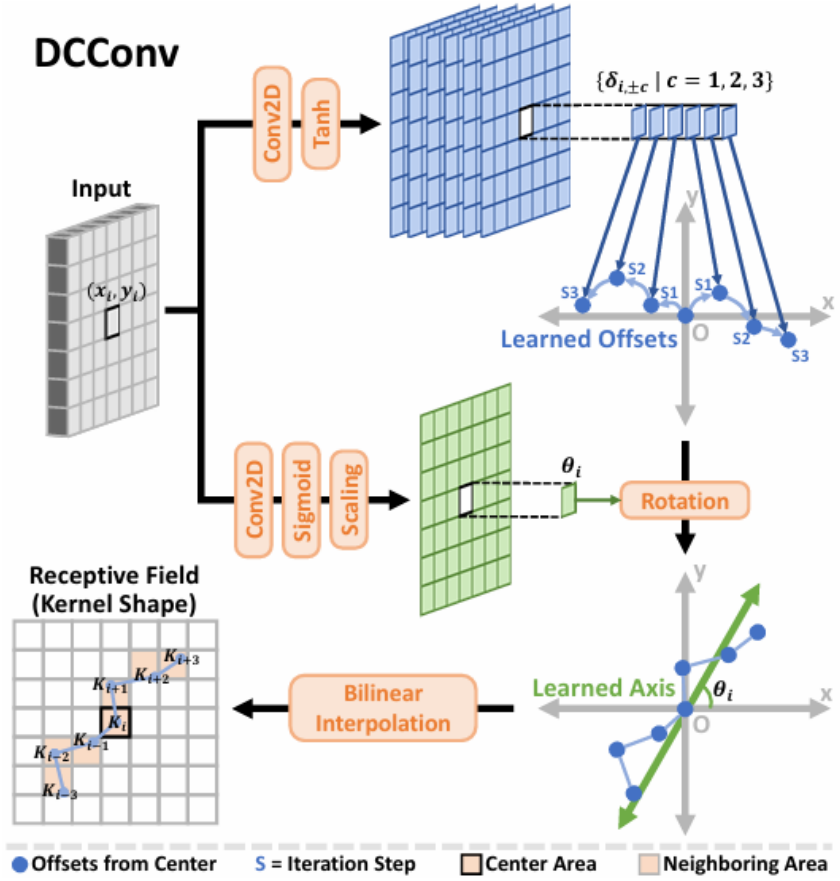
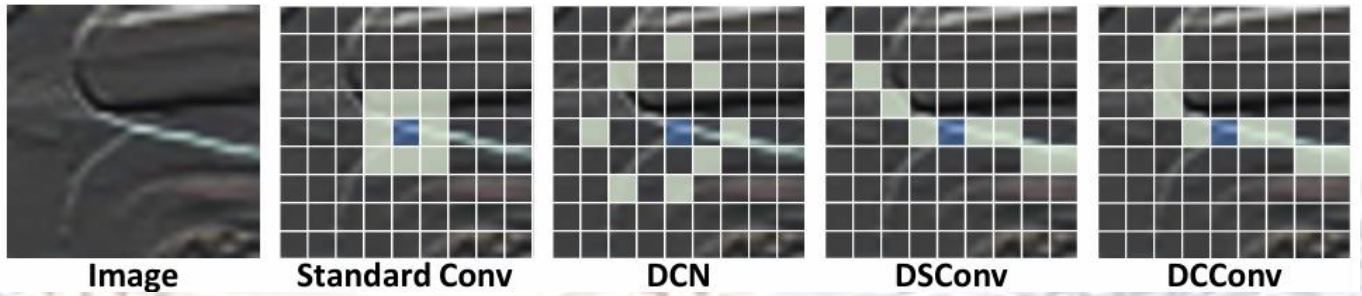


Figure 6: Schematic diagram of the proposed DCConv, initialized along the x-axis. Our method predicts both the offsets and axis orientations simultaneously, allowing for the effective representation of slender structures aligned in arbitrary directions. For illustration, the kernel length k is set to 7.

$$K_{i\pm c} = (x_i, y_i) + (\pm c, \sum_{j=0}^{c} \delta_{i,\pm j}) \cdot \begin{bmatrix} \cos\theta_i & \sin\theta_i \\ -\sin\theta_i & \cos\theta_i \end{bmatrix}$$

$$K_{i\pm c} = (x_i, y_i) + (\sum_{j=0}^{c} \delta_{i,\pm j}, \pm c) \cdot \begin{bmatrix} \cos\theta_i & \sin\theta_i \\ -\sin\theta_i & \cos\theta_i \end{bmatrix}.$$



WMamba: VMamba

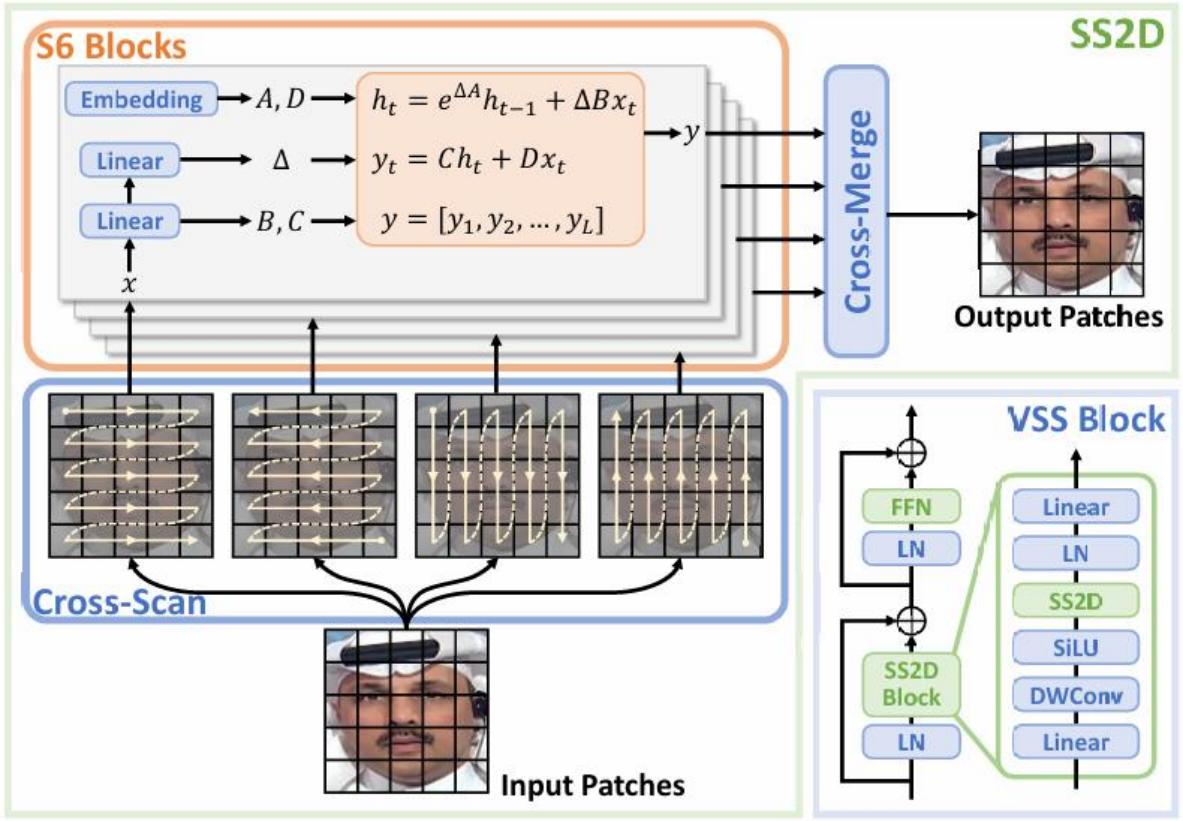
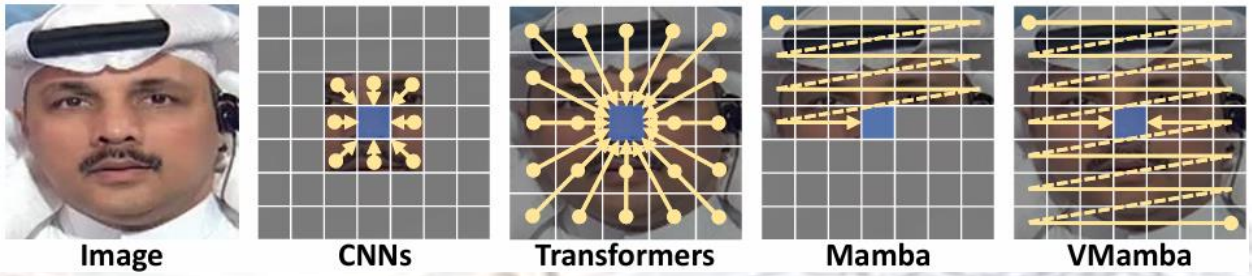


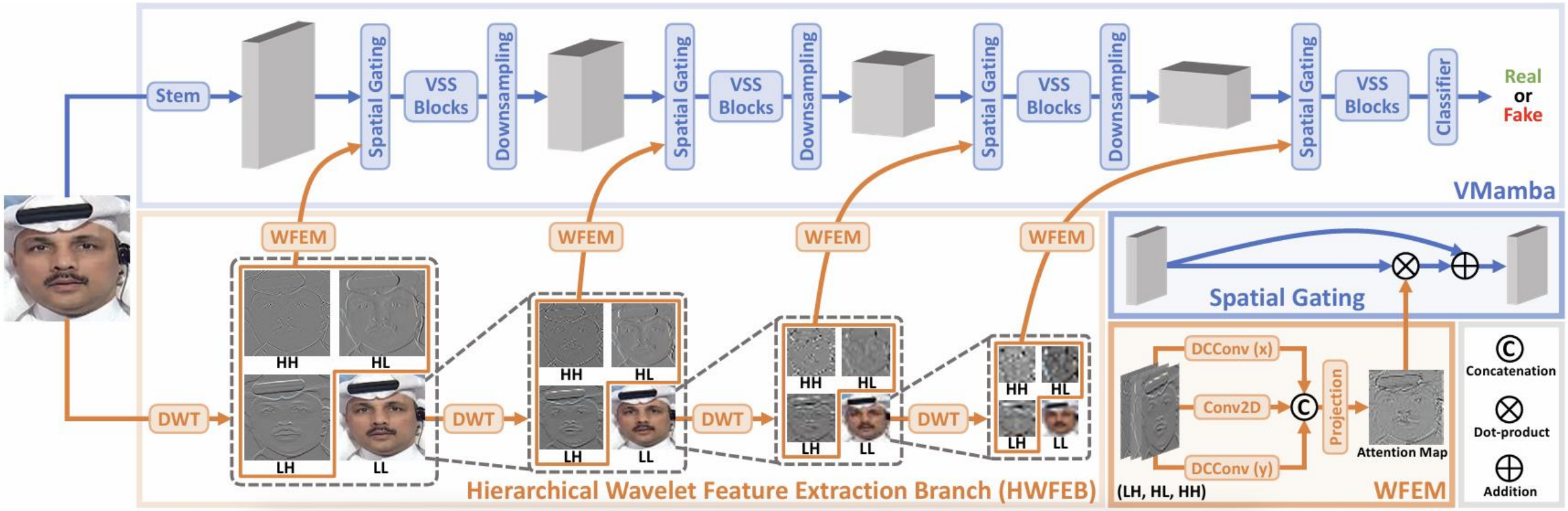
Figure 5: Schematic diagram of the VSS block, with the SS2D mechanism at its core. This mechanism flattens input image patches along four principle directions, facilitating comprehensive global perception. L denotes the number of patches.

$$h_t = \overline{A} h_{t-1} + \overline{B} x_t,$$
$$y_t = C h_t + D x_t.$$

$$\overline{A} = e^{\Delta A},$$
$$\overline{B} = (\Delta A)^{-1}(e^{\Delta A} - E) \cdot \Delta B \approx \Delta B.$$



WMamba: Architecture



WMamba: Results

Training set: FF++

Cross-Dataset

Method	Venue	Input Type	Training Set		Test Set AUC (%)			
			Real	Fake	CDF	DFDC	DFDCP	FFIW
F^3-Net* [43]	ECCV 2020	Frame	✓	✓	77.92	67.35	73.54	70.11
LTW* [49]	AAAI 2021	Frame	✓	✓	77.14	69.00	74.58	76.63
PCL+I2G [65]	ICCV 2021	Frame	✓		90.03	67.52	74.37	-
DCL [50]	AAAI 2022	Frame	✓	✓	82.30	-	76.71	71.14
SBI [46]	CVPR 2022	Frame	✓		93.18	72.42	86.15	84.83
F^2Trans [36]	TIFS 2023	Frame	✓	✓	89.87	-	76.15	-
SeeABLE [25]	ICCV 2023	Frame	✓		87.30	75.90	86.30	-
AUNet [1]	CVPR 2023	Frame	✓		92.77	73.82	86.16	81.45
LAA-Net [37]	CVPR 2024	Frame	✓		95.40	-	86.94	-
RAE [54]	ECCV 2024	Frame	✓		<u>95.50</u>	80.20	<u>89.50</u>	-
FreqBlender [67]	NeurIPS 2024	Frame	✓		94.59	74.59	87.56	<u>86.14</u>
UDD [10]	AAAI 2025	Frame	✓	✓	93.10	<u>81.20</u>	88.10	-
LESB [48]	WACVW 2025	Frame	✓		93.13	71.98	-	83.01
FTCN* [66]	ICCV 2021	Video	✓	✓	86.90	71.00	74.00	74.47
RealForensics [16]	CVPR 2022	Video	✓	✓	86.90	-	75.90	-
TALL [56]	ICCV 2023	Video	✓	✓	90.79	-	76.78	-
TALL++ [57]	IJCV 2024	Video	✓	✓	91.96	-	78.51	-
NACO [63]	ECCV 2024	Video	✓	✓	89.50	-	76.70	-
WMamba (Ours)	-	Frame	✓		**96.29**	**82.97**	**89.62**	**86.59**

Cross-Manipulation

Method	Test Set AUC (%)				
	DF	F2F	FS	NT	FF++
PCL+I2G [65]	**100**	98.97	99.86	97.63	99.11
SBI [46]	<u>99.99</u>	<u>99.88</u>	<u>99.91</u>	<u>98.79</u>	<u>99.64</u>
SeeABLE [25]	99.20	98.80	99.10	96.90	98.50
AUNet [1]	99.98	99.60	99.89	98.38	99.46
RAE [54]	99.60	99.10	99.20	97.60	98.90
WMamba	**100**	**99.98**	**99.94**	**98.88**	**99.70**

WMamba: Results

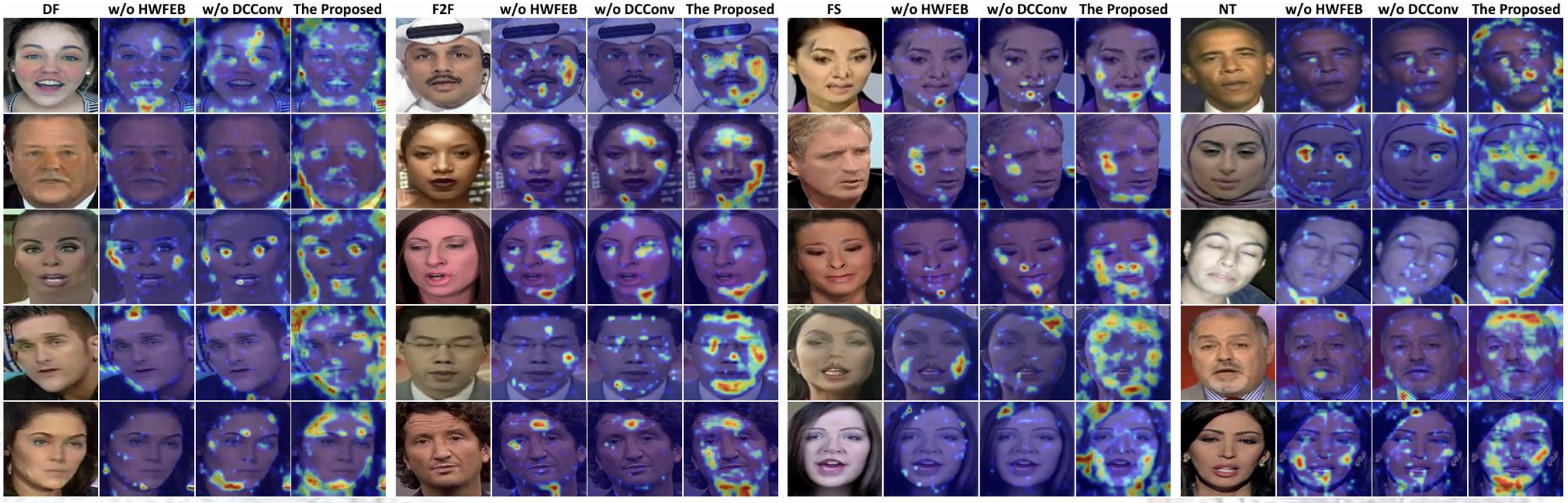


Figure 2: Saliency maps for a variety of fake samples from the FF++ dataset, where redder regions indicate areas of higher model attention. The HWFEB and DCConv effectively direct our model's attention toward critical facial contours.

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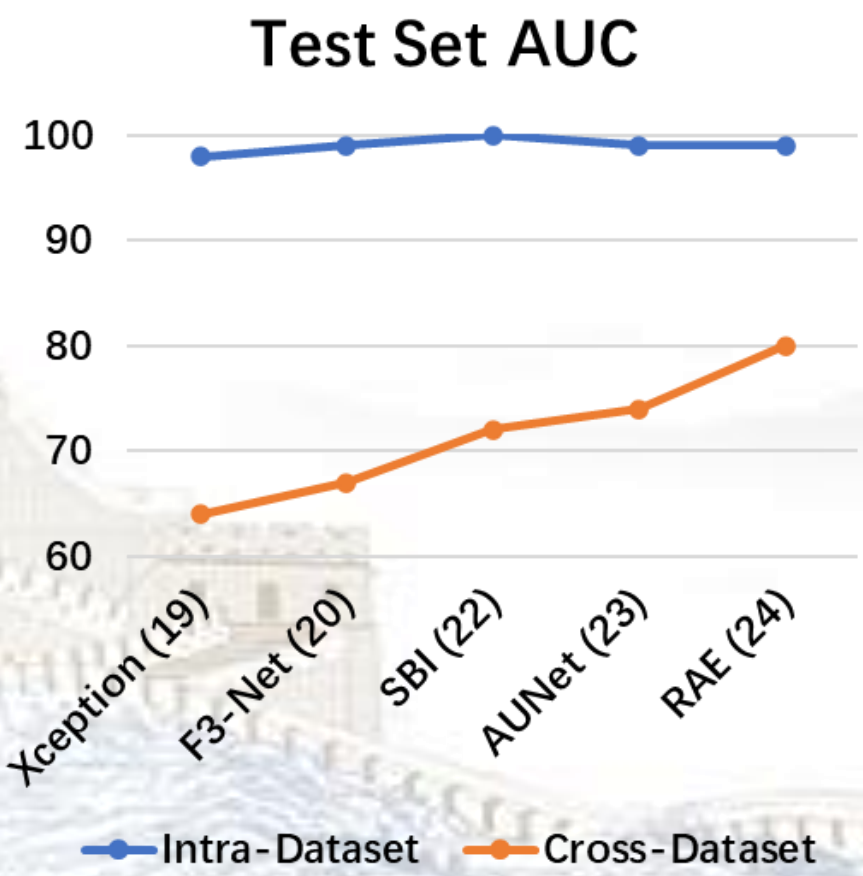
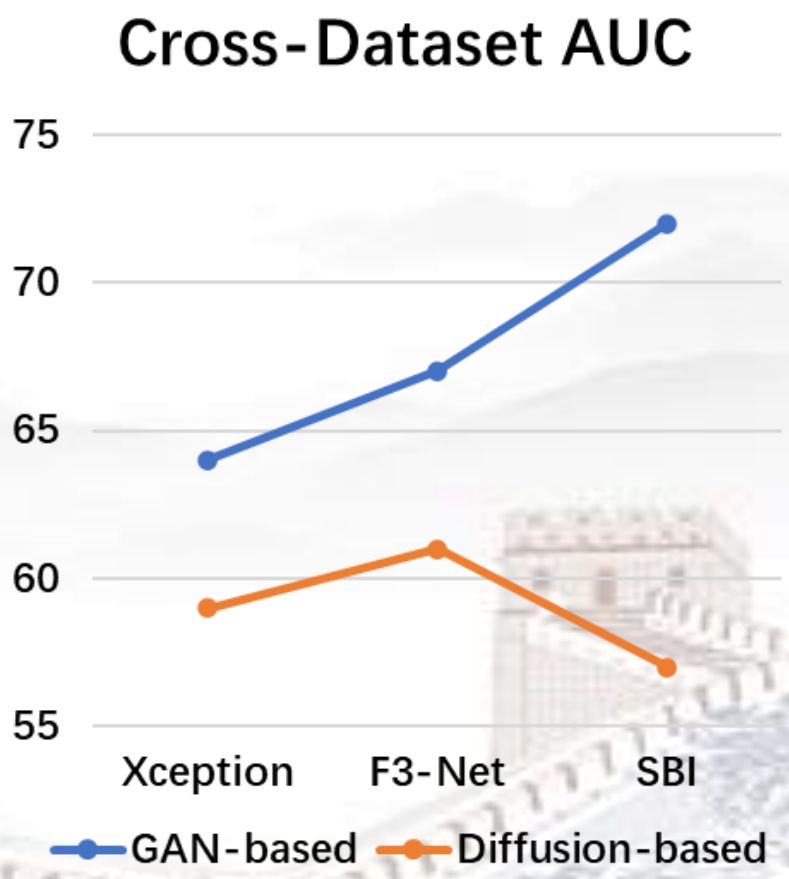
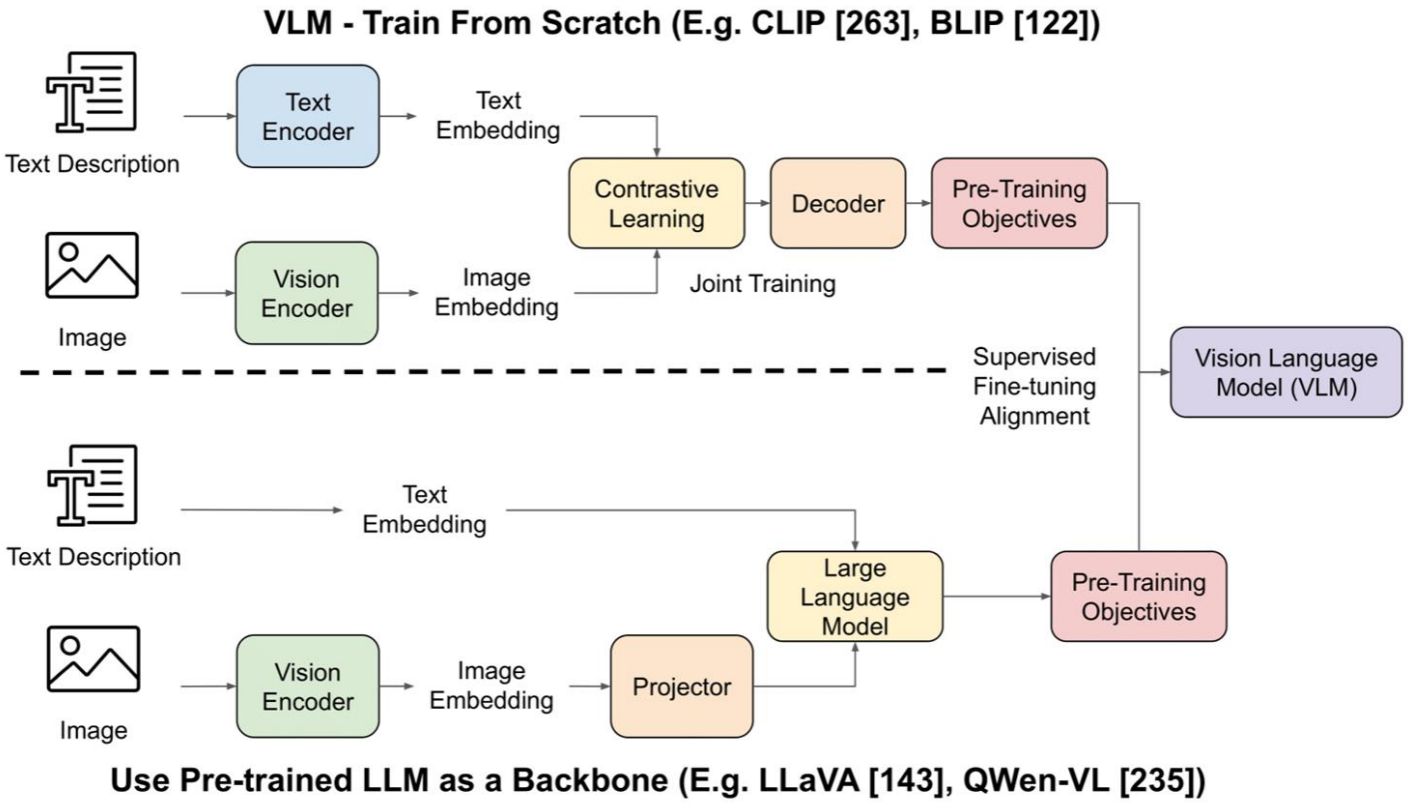
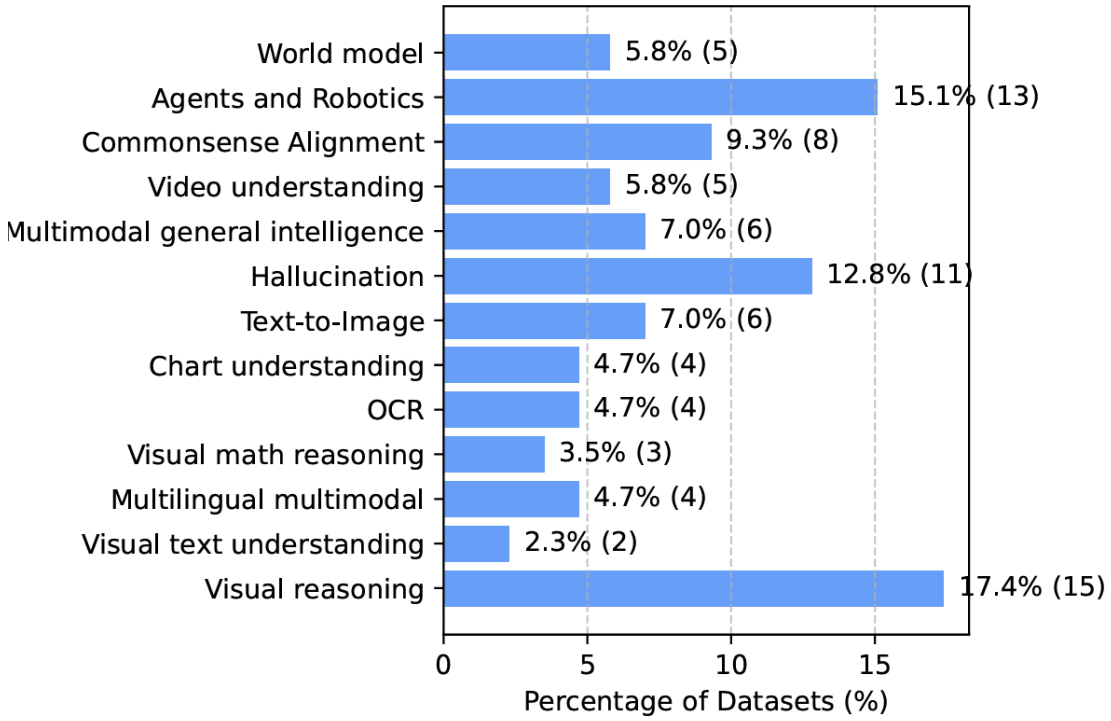
Background: Generalization



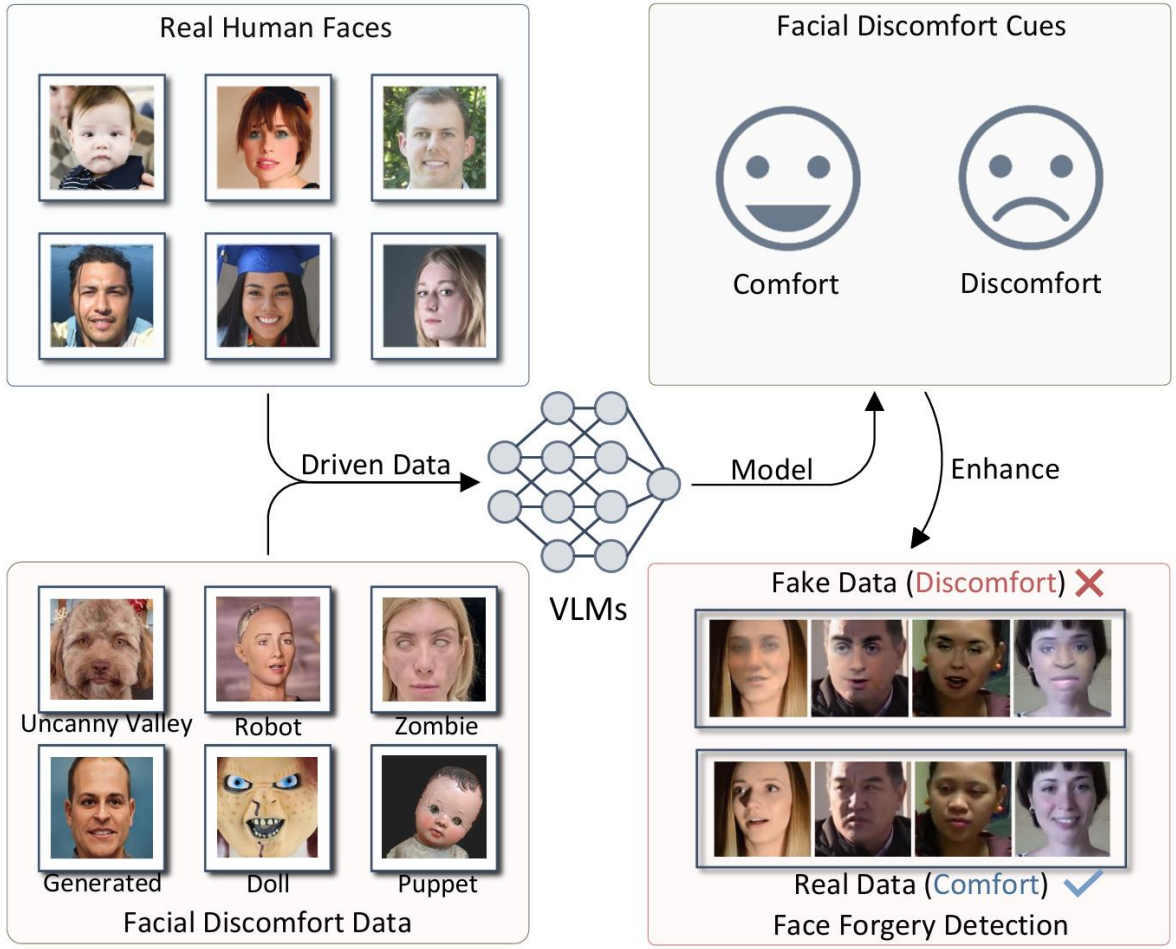


FDJL: Motivation

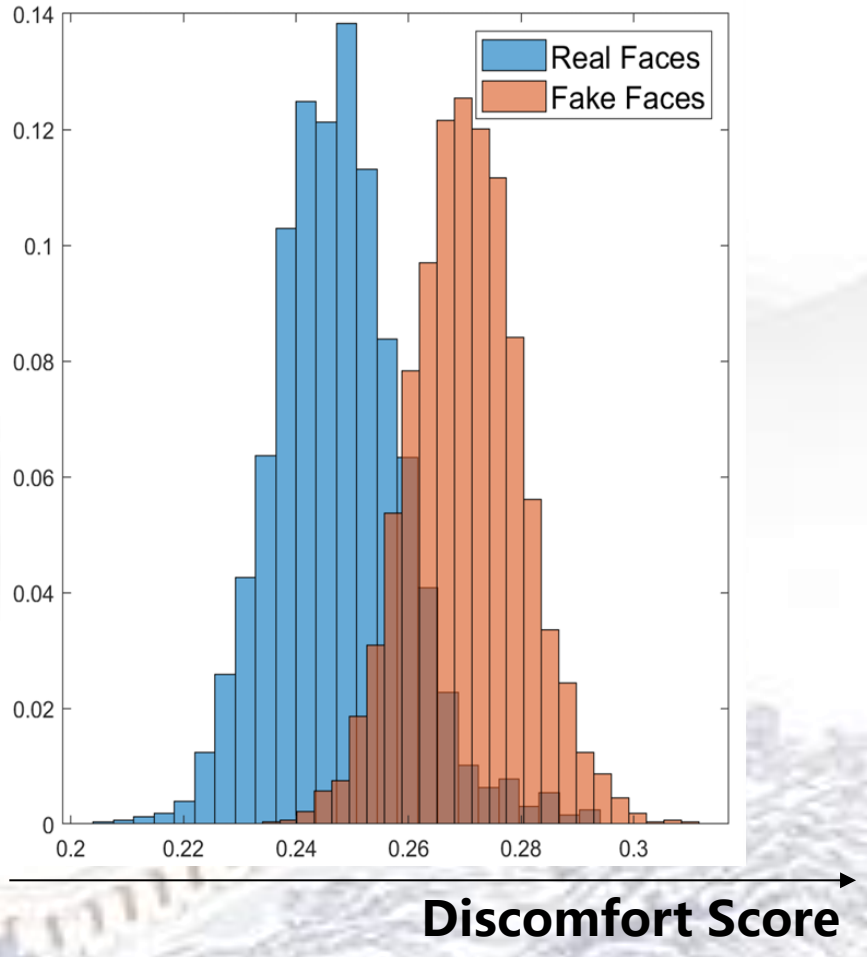




FDJL: Motivation

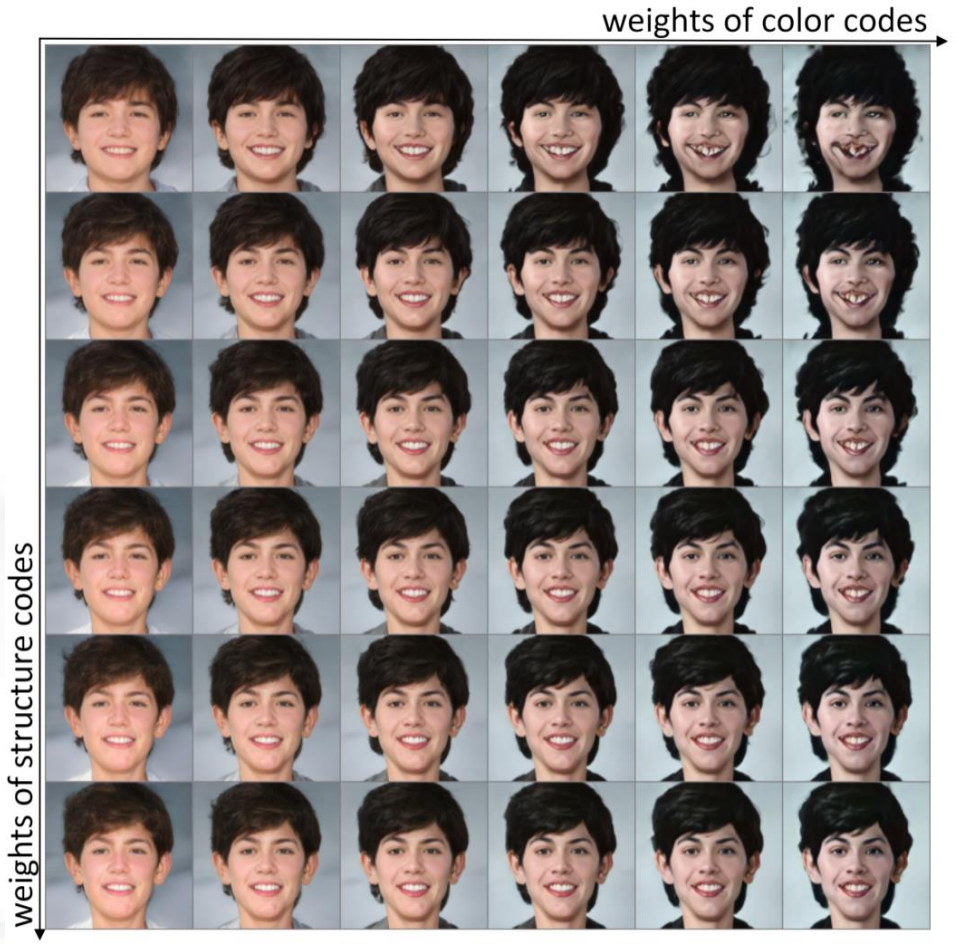


' A weird photo that may cause fear and discomfort '



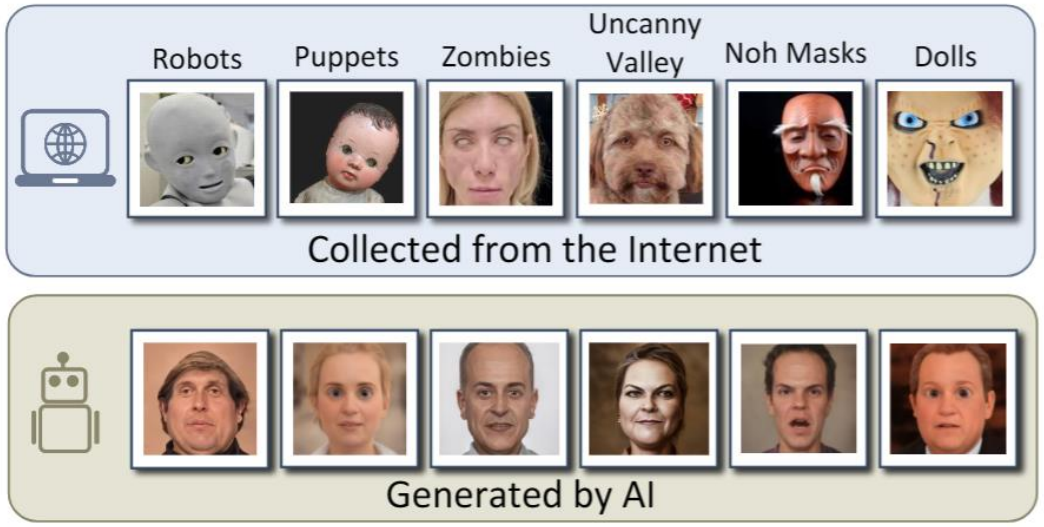
Facial Discomfort Dataset

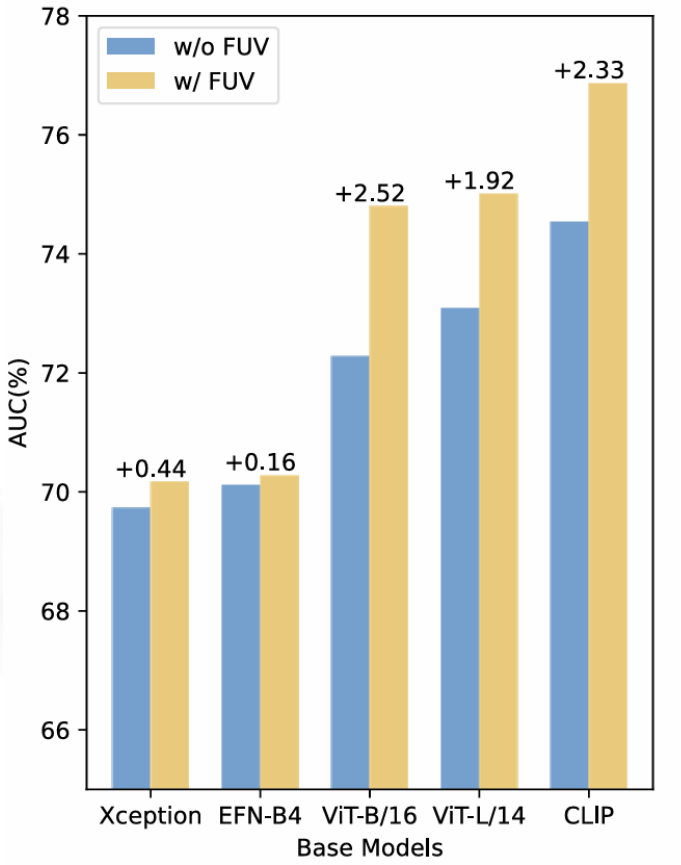
Collecting data from the Internet



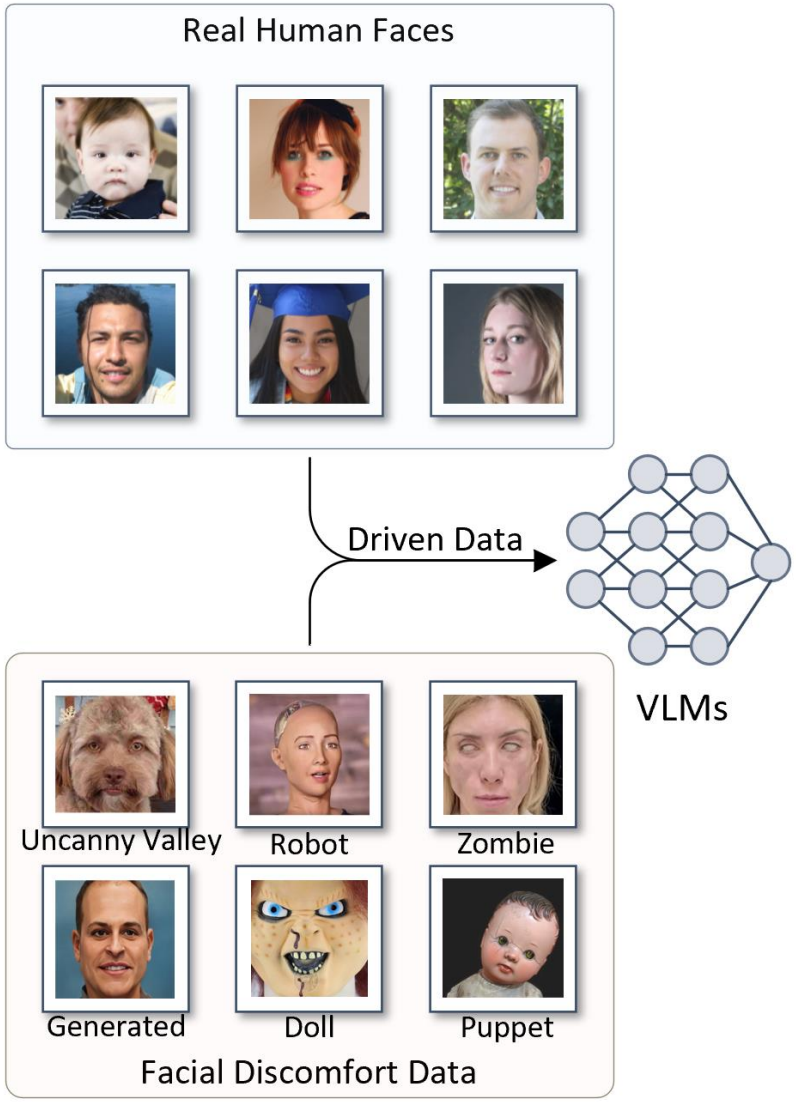
Generating data utilizing AIGC Models

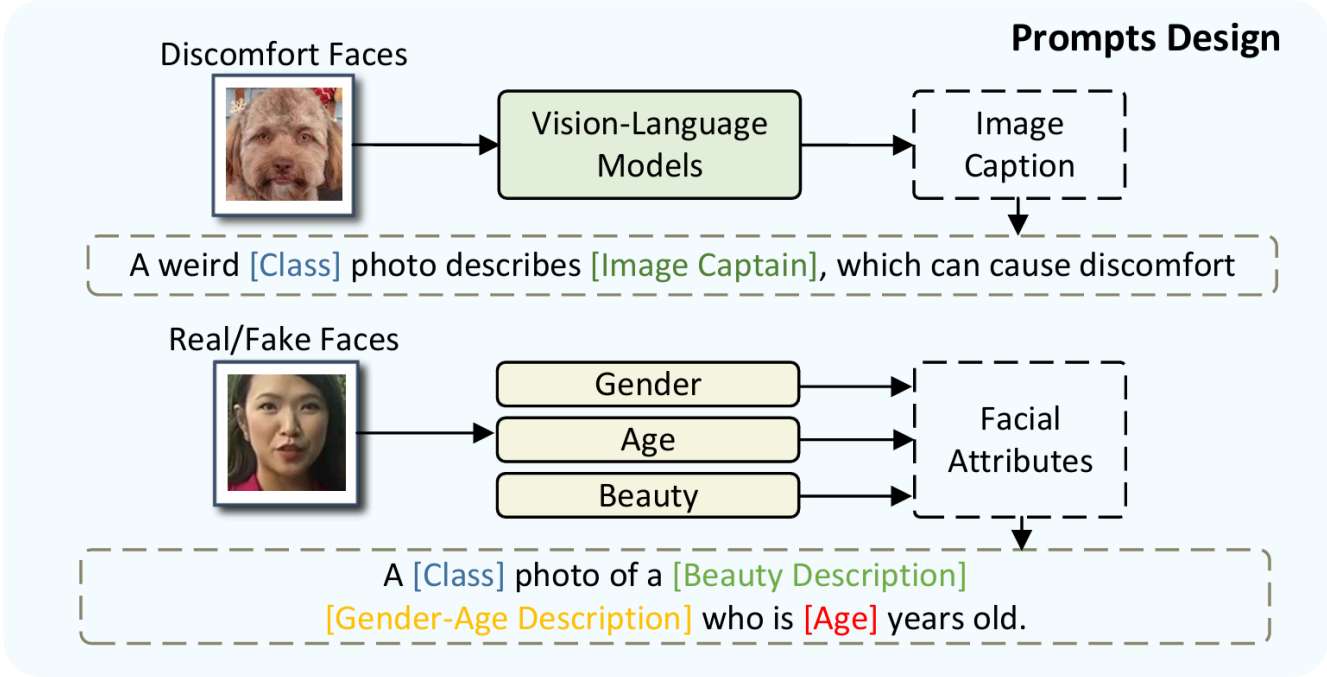
Facial Discomfort Dataset



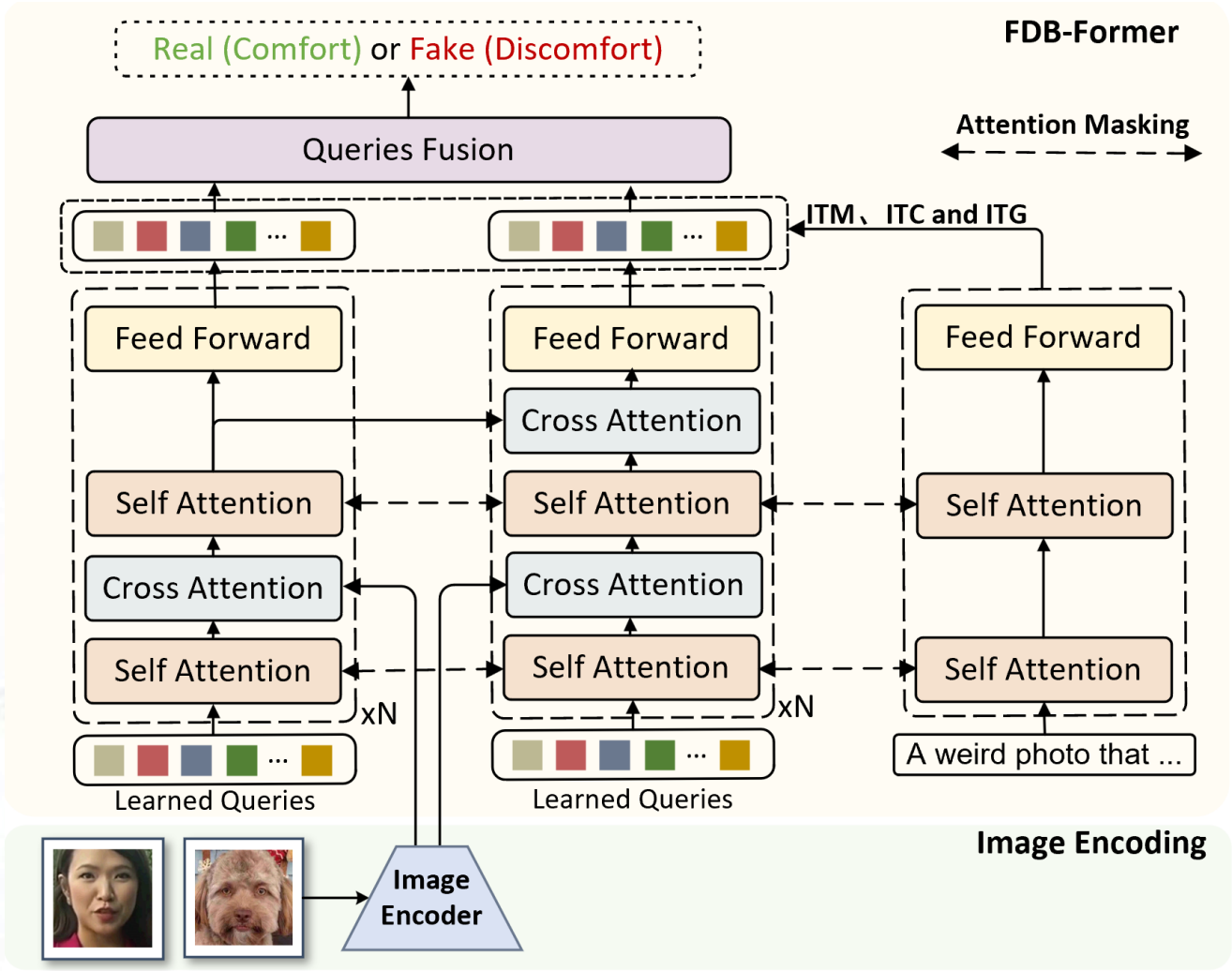


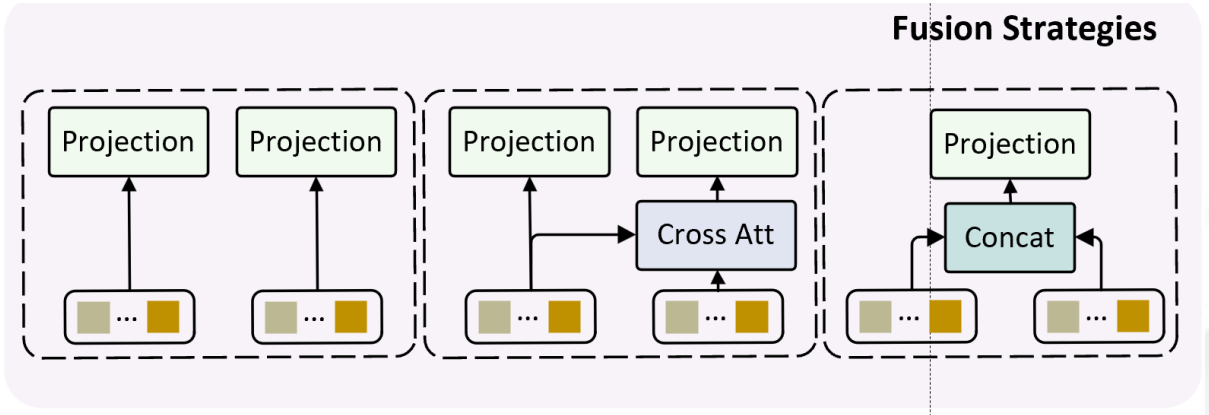
Prompts Design

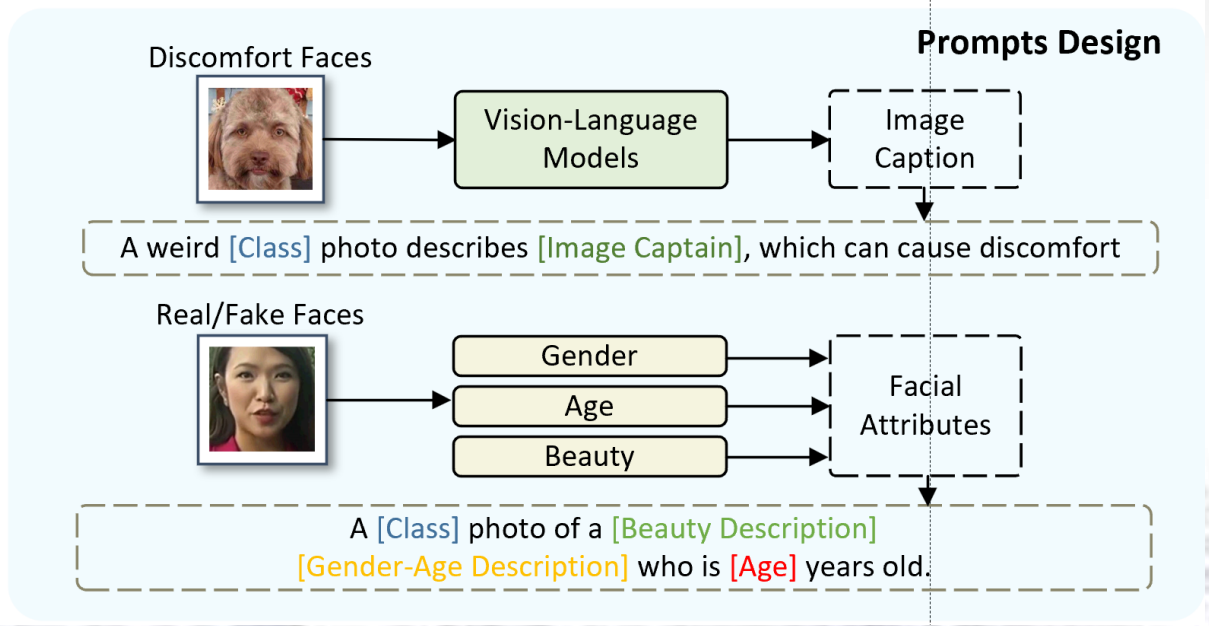




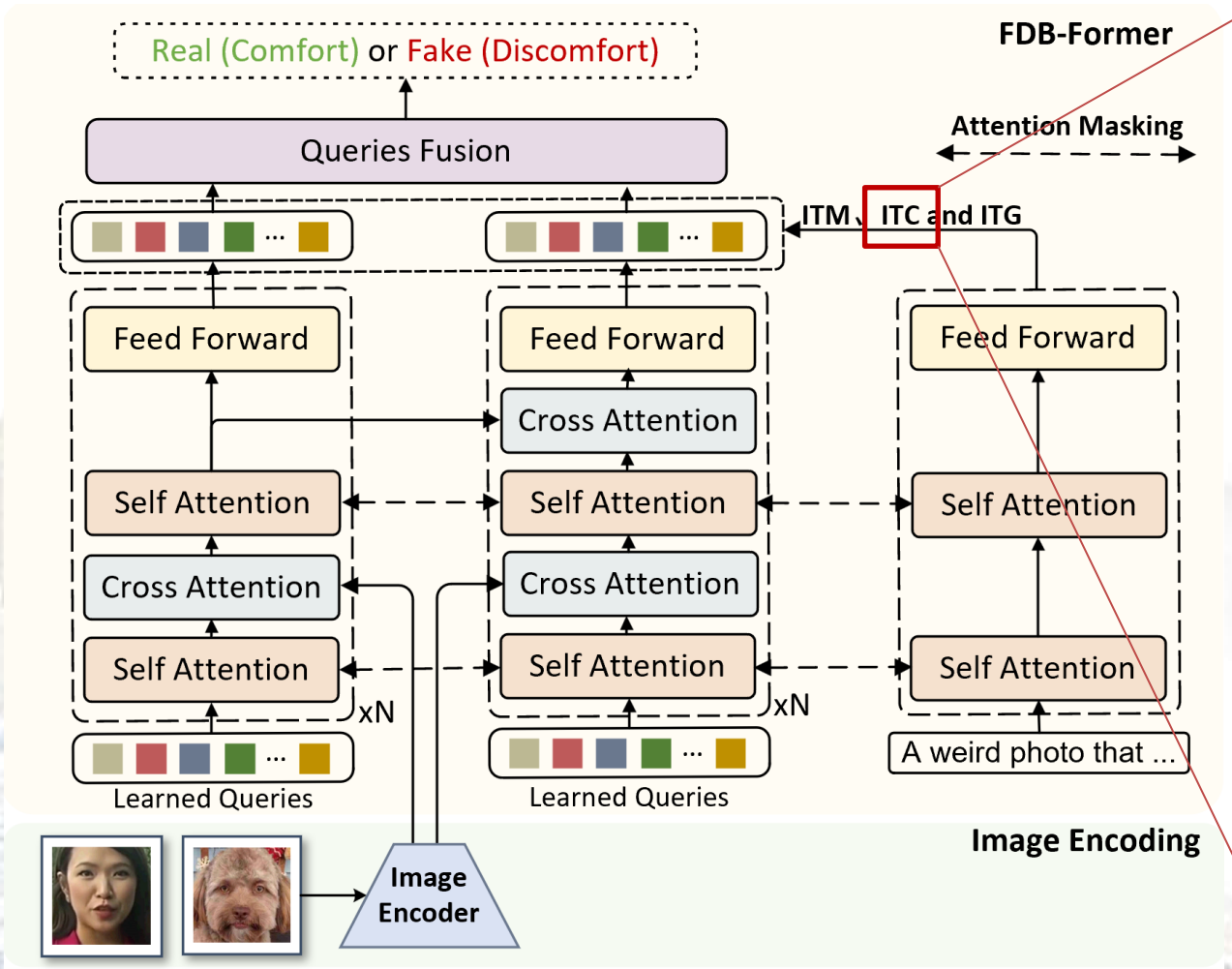
Forgery-Discomfort Joint Learning

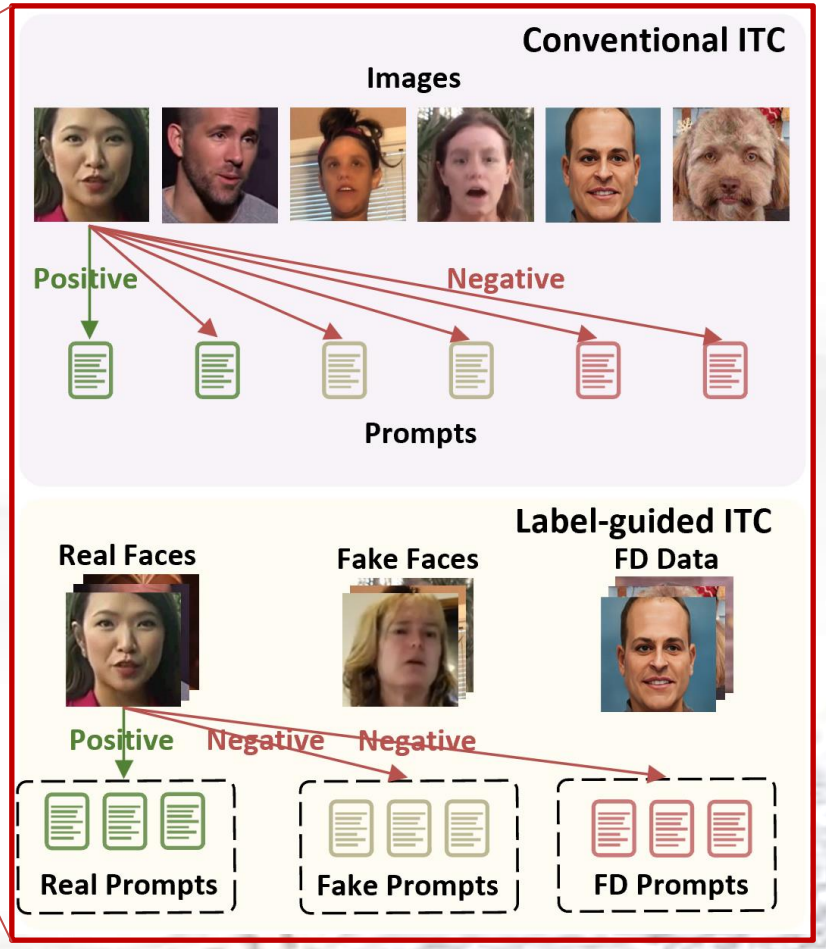




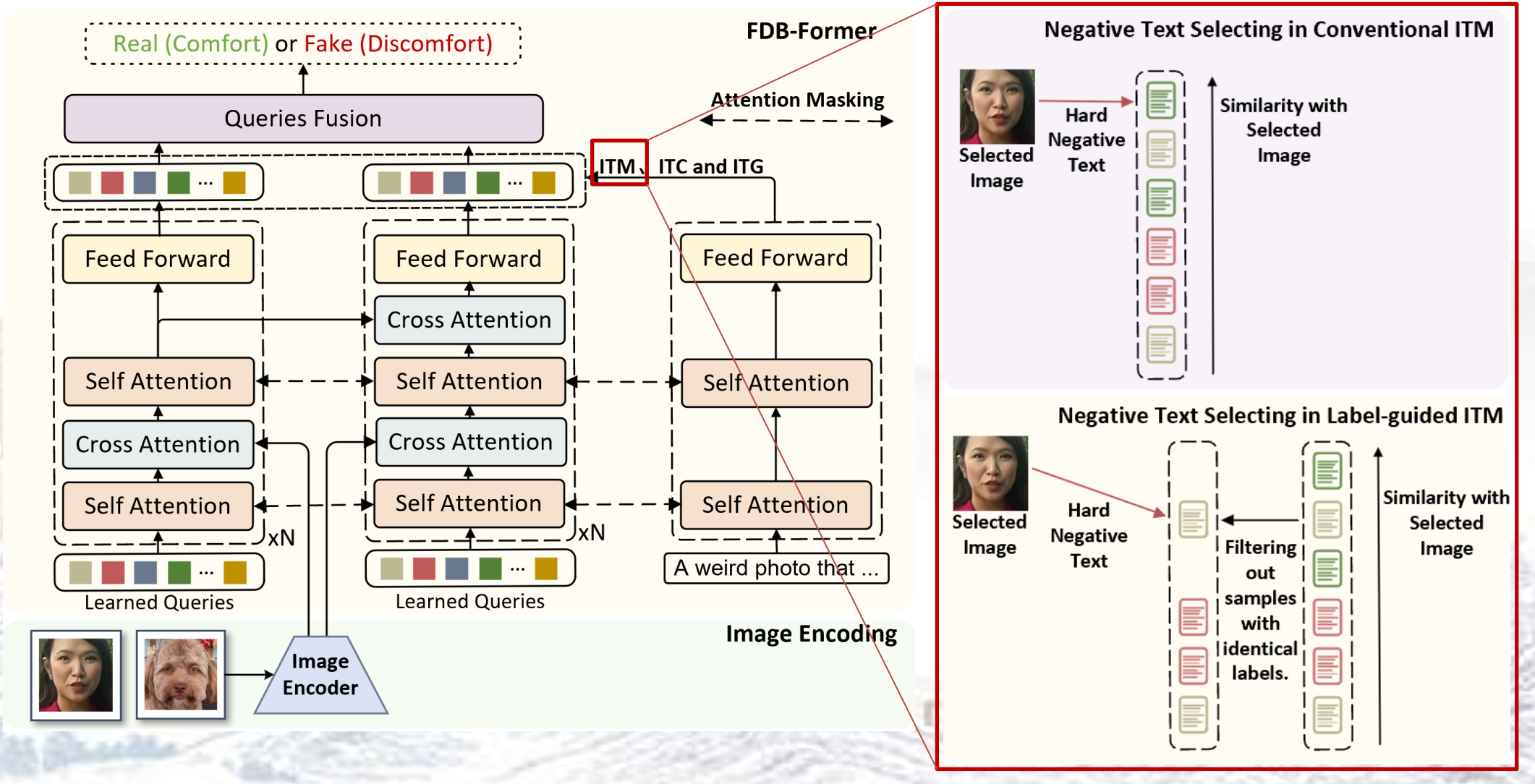


Forgery-Discomfort Joint Learning





Forgery-Discomfort Joint Learning



FDJL: Results

Table 1. Comparison experiments under the standard cross-dataset testing protocol. Methods marked with the symbol $*$ are reproduced using the official codes. The best performance is highlighted in **bold**, and the second best is underlined. The testing results show that the proposed FDJL framework achieves state-of-the-art results among all the compared methods, including methods that take frames and videos as input.

Method	Input Type	Training Set		Test Set AUC (%)			
		Real	Fake	Celeb-DF	DFDC	DFDCP	FFIW
Xception* [3]	Frame	✓	✓	65.27	69.73	73.74	59.45
Face X-ray+BI [17]	Frame	✓	✓	79.50	65.50	80.92	-
F^3-Net* [23]	Frame	✓	✓	77.92	67.35	73.54	70.11
LTW* [28]	Frame	✓	✓	77.14	69.00	74.58	76.63
PCL+I2G [6]	Frame	✓		90.03	67.52	74.37	-
CORE [22]	Frame	✓		79.45	72.83	75.74	75.19
DCL [29]	Frame	✓	✓	82.30	76.71	-	-
SBI [27]	Frame	✓		93.18	72.42	86.15	<u>84.83</u>
F^2Trans [19]	Frame	✓	✓	89.87	76.15	-	-
SeeABLE [15]	Frame	✓		87.30	75.90	86.30	-
AUNet [1]	Frame	✓		92.77	73.82	86.16	81.45
MoE-FFD [14]	Frame	✓	✓	91.28	-	84.97	-
UCF [37]	Frame	✓	✓	82.40	80.50	-	-
LAANet [21]	Frame	✓		95.40	-	86.94	-
RAE [33]	Frame	✓		<u>95.50</u>	<u>80.20</u>	<u>89.50</u>	-
FTCN* [40]	Video	✓	✓	86.90	71.00	74.00	74.47
RealForensics [8]	Video	✓	✓	86.90	75.90	-	-
TALL [35]	Video	✓	✓	90.79	76.78	-	-
TALL++ [36]	Video	✓	✓	91.96	78.51	-	-
NACO [38]	Video	✓	✓	89.50	76.70	-	-
Ours(FDJL+FD dataset)	Frame	✓		**95.62**	**81.91**	**89.58**	**86.74**

FDJL: Results

Table 2. Comparative experiments when facing unknown forgery methods. All methods are reproduced using the official codes. The best performance is highlighted in **bold**, and the second best is underlined. Our FJDL achieves state-of-the-art results among all the compared methods, indicating that the proposed method performs better generalization for unknown forgery types.

Method	AUC (%)					
	2D Face Morphing				3D Face Morphing	Face Generation
	OpenCV	Face Morpher	Web Morph	AMSL	Shape Transfer	StyleGAN2
MOCO [9]	57.80	54.44	50.51	52.72	49.91	43.25
CLIP [24]	67.56	72.64	68.04	73.33	63.25	70.71
OC-FakeDect [11]	69.74	70.57	63.81	66.35	60.37	56.61
Xception [3]	63.03	57.39	55.76	51.13	51.84	53.23
EfficientNetB4 [2]	59.23	59.34	52.69	54.91	52.69	55.08
LTW [28]	74.67	63.00	62.81	61.09	57.86	61.10
F^3-Net [23]	71.99	67.19	65.77	64.02	55.30	63.48
CORE [22]	74.89	69.11	70.47	68.87	64.57	67.14
STDD [39]	73.15	66.95	67.56	65.63	61.59	65.35
FaRL [41]	75.76	74.20	69.84	67.43	67.69	68.88
FakeOut [13]	77.31	71.52	66.04	68.93	64.46	68.13
DCL [29]	79.65	74.91	71.39	70.26	71.61	70.84
SBI [27]	81.72	78.65	72.50	71.69	70.12	66.97
Ours(FDJL+FD dataset)	**87.25**	**81.86**	**75.56**	**74.92**	**74.73**	**79.83**

FDJL: Results

Train	Method	DF	F2F	FS	NT
DF	EN-b4	*99.97*	76.32	46.24	72.72
	DCL	*99.98*	77.13	61.01	75.01
F2F	EN-b4	84.52	*99.20*	58.14	63.71
	DCL	91.91	*99.21*	59.58	66.67
FS	EN-b4	69.25	67.69	*99.89*	48.61
	DCL	74.80	69.75	*99.90*	52.60
NT	EN-b4	85.99	48.86	73.05	*98.25*
	DCL	91.23	52.13	79.31	*98.97*
BI	Face X-ray	99.17	98.57	98.21	98.13
SBIS	SBI	**99.99**	99.88	99.91	98.79
SBIs+FD	Ours	99.98	**99.97**	**99.93**	**99.04**

FDJL: Ablation Study

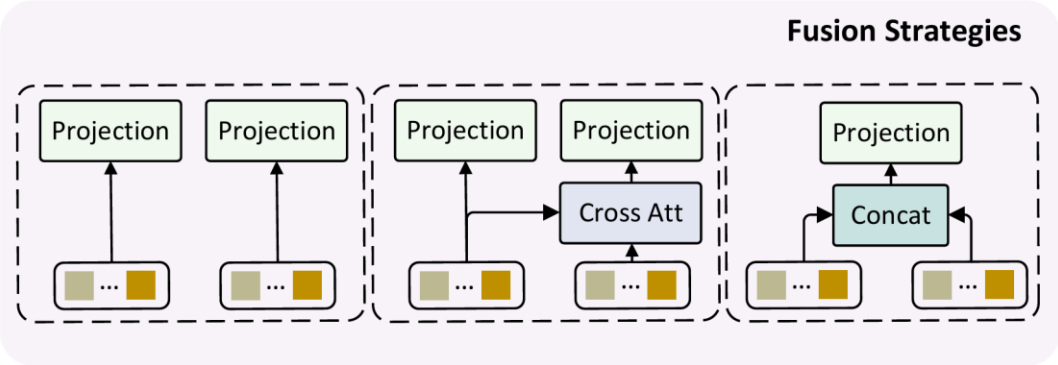


Table 4. Ablation study of the Facial Discomfort dataset.

Collected	Generated	AUC(%)			
		Celeb-DF	DFDC	DFDCP	FFIW
		91.93	74.28	79.72	77.46
✓		94.47	78.17	87.40	82.50
	✓	93.82	76.70	83.05	82.98
✓	✓	**95.62**	**81.91**	**89.58**	**86.74**

Table 6. Ablation study on fusion strategies.

Fusion Strategy	AUC(%)			
	Celeb-DF	DFDC	DFDCP	FFIW
Concat	87.36	74.69	76.58	69.89
Cross-Att	94.60	81.41	88.66	85.51
Split	**95.62**	**81.91**	**89.58**	**86.74**

Table 5. Ablation study on the different losses.

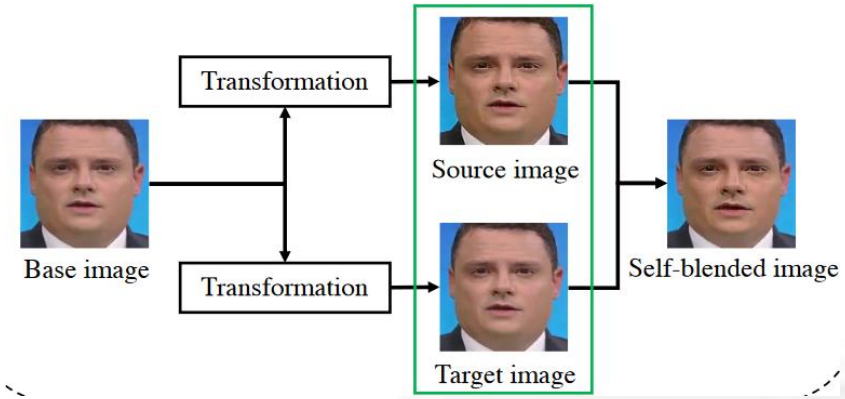
$\mathcal{L}_{CLS}$	$\mathcal{L}_{ITA}$	$\mathcal{L}_{FD}$	AUC(%)			
			Celeb-DF	DFDC	DFDCP	FFIW
✓			87.50	69.73	75.90	73.02
✓	✓		92.11	75.59	76.17	80.85
✓		✓	91.93	73.75	78.14	82.19
✓	✓	✓	**95.62**	**81.91**	**89.58**	**86.74**

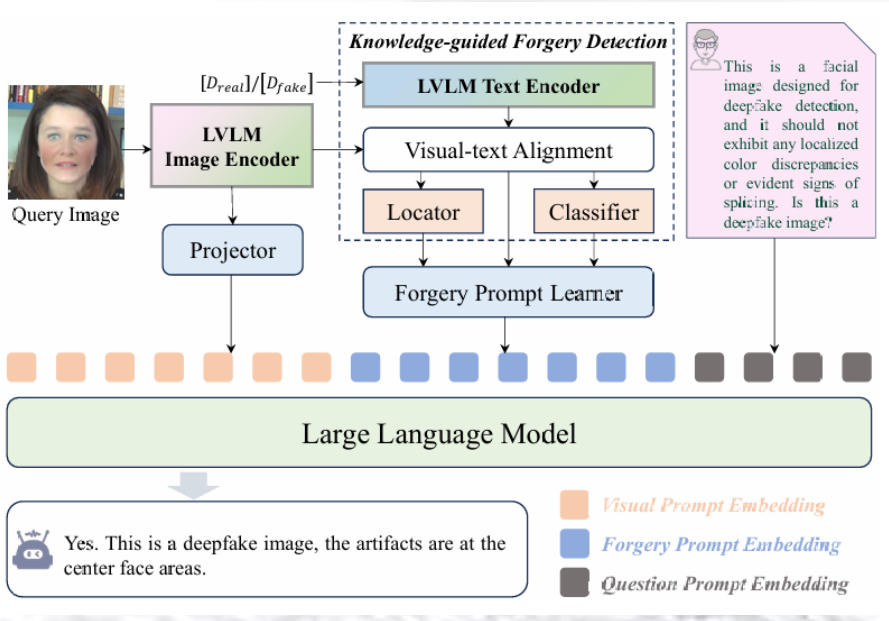
Take home message

- Robust and discriminant features for deepfake detection is necessary. Combining different types for features (e.g., semantic and detailed features) is a possible way .

- Fundamental (essential) features rather than database biased features is the key to realize high generalization performance.

- Multi-modal large model is a promising direction. Not only output the classification results, but also with explainable texts.





Thank You!