ICCV23
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paper & code

Towards Generic Image Manipulation Detection with Weakly-Supervised Self-Consistency Learning

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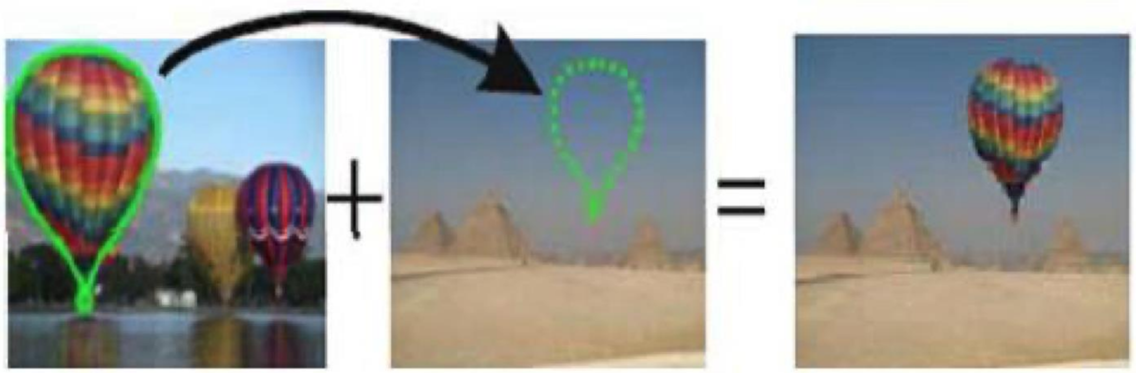
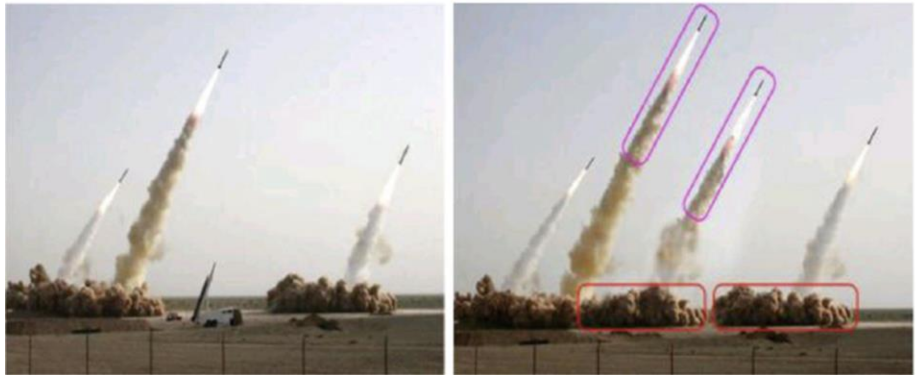
Image manipulations



Splicing [Sharma et al.]



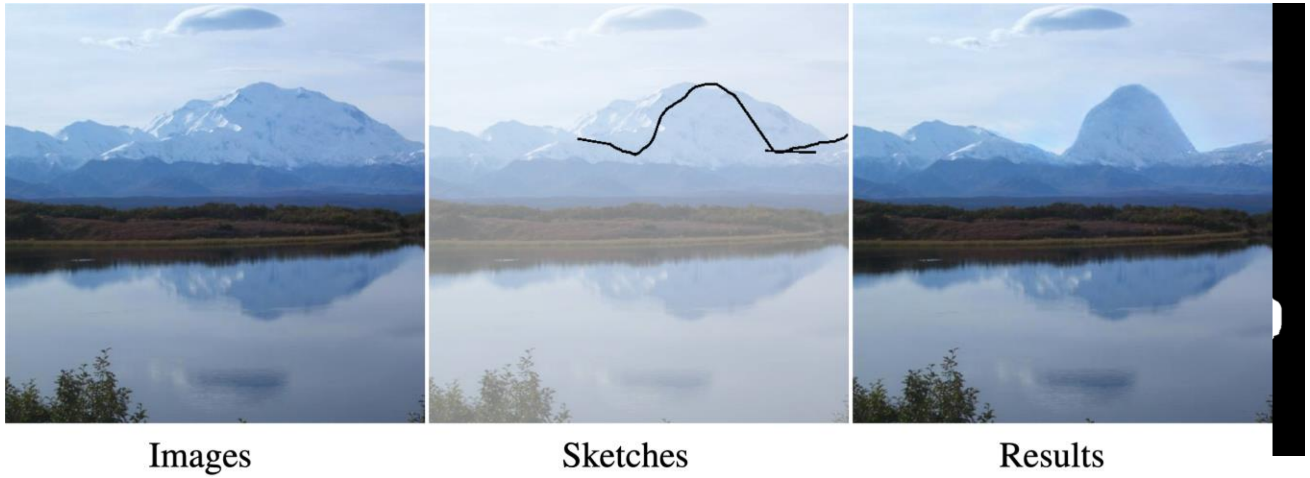
Copy-move [Mahdi et al.]

Inpainting [Trung et al.]

Image manipulations (cont’d)

- Splicing, copy-move and inpainting all have **pixel-level** masks
  - Detection model trained with pixel-level mask can precisely locate manipulations
- Emerging editing methods, such as language-guided or sketch-based methods, do not necessarily generate such masks

[Wang et al.]
[Wen et al.]



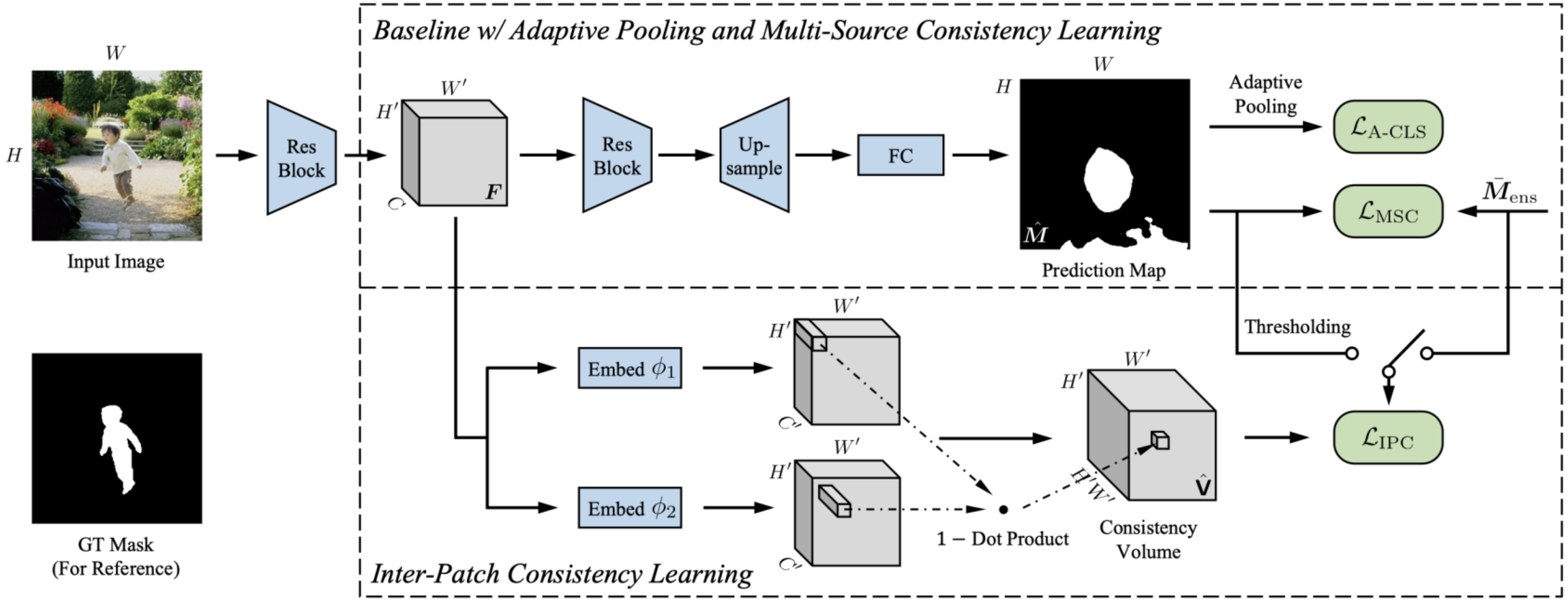
[Guang et al.]
[Zeng et al.]

Weakly-supervised image manipulation detection (W-IMD)

- Given only **binary image-level labels** (real or fake), predict whether an image is manipulated, and localize the manipulation at the pixel level.

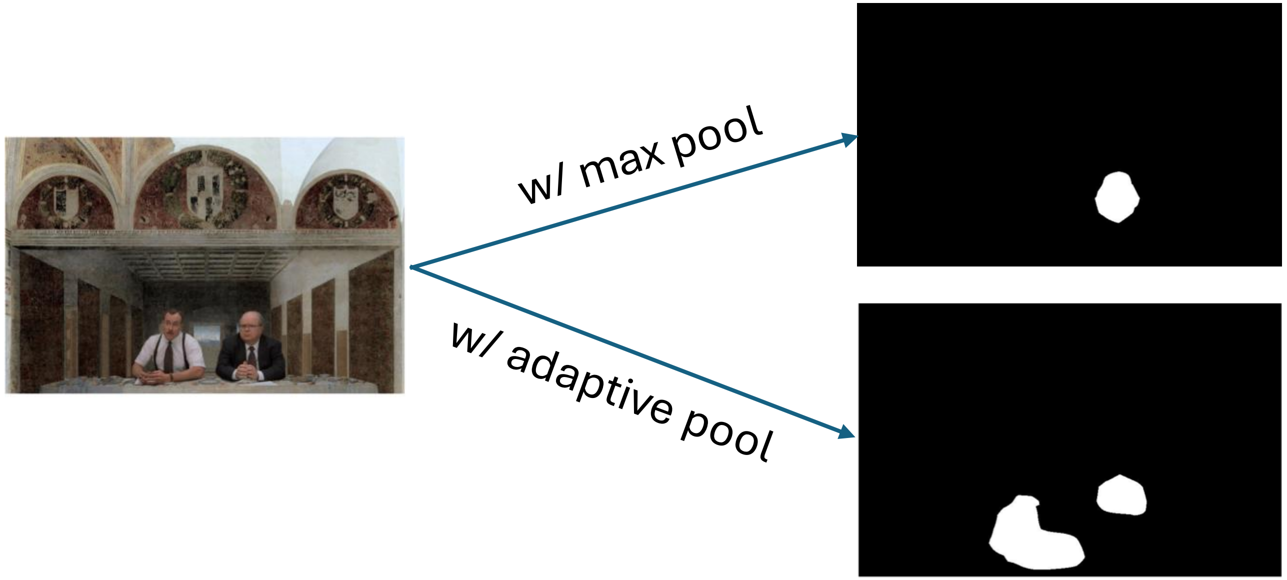
Weakly-supervised self-consistency learning

- Adaptive pooling
- Multi-source consistency
- Inter-patch consistency



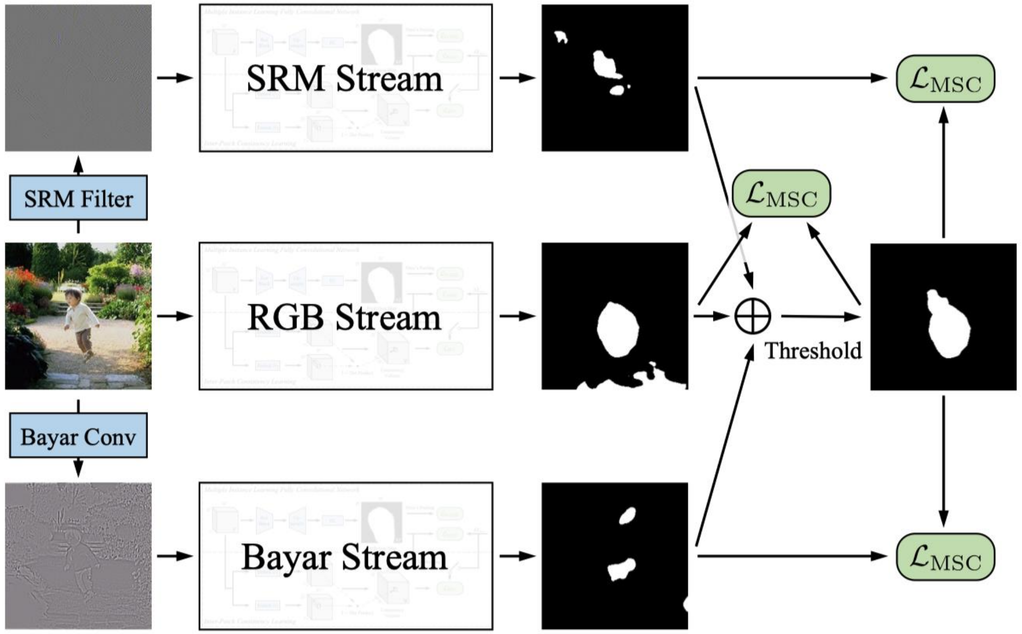
Adaptive pooling

- Max-pooling can only detect the most salient manipulation
- Adaptive pooling dynamically selects the portion with high activations
  - Ostu’s method for select the high-activation group
  - Average pooling on the high-activation group



Multi-source consistency (MSC)

- Fuse information from different noise sources
- The ensemble prediction is in turn used as pseudo ground truth, and supervise each individual stream



Inter-patch consistency

- Global patch-patch similarity is computed by pair-wise patch feature dot product, and forms a 4D consistency volume
- The pseudo ground truth from MSC is used to supervise the consistency volume to enhance low-level feature

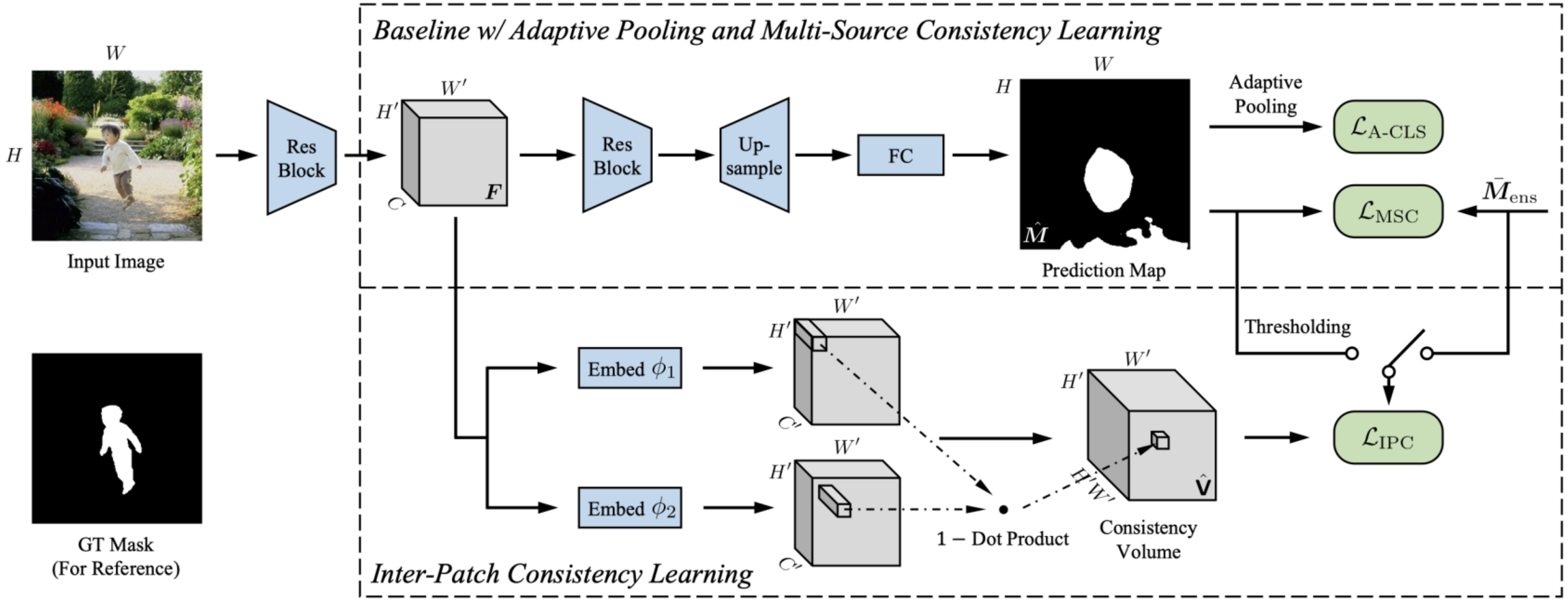
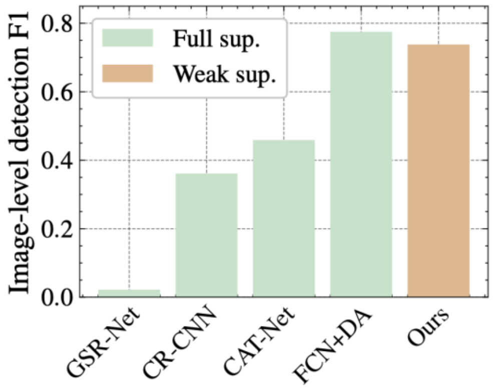
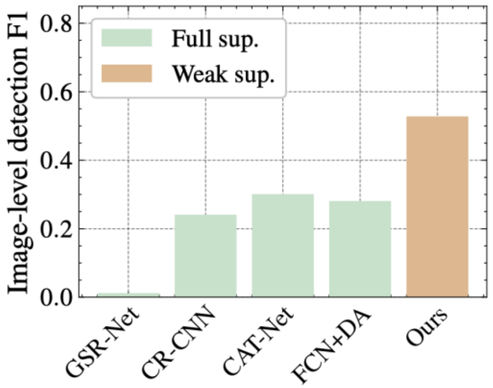


Image-level manipulation detection

- Best average AUC and F1
- Our method better generalizes to OOD manipulations





	Method	CASIAv1				Columbia				Coverage				IMD2020				Avg	
		AUC	Spe.	Sen.	I-F1	AUC	Spe.	Sen.	I-F1	AUC	Spe.	Sen.	I-F1	AUC	Spe.	Sen.	I-F1	AUC	I-F1
Un.	NOI1 [29]	0.500	0.000	1.000	0.000	0.500	0.000	1.000	0.000	0.500	0.000	1.000	0.000	0.500	0.000	1.000	0.000	0.500	0.000
	CFA1 [13]	0.482	0.000	1.000	0.000	0.344	0.000	1.000	0.000	0.525	0.000	1.000	0.000	0.500	0.000	1.000	0.000	0.500	0.000
Full	Mantra-Net [55]	0.141	0.000	1.000	0.000	0.701	0.000	1.000	0.000	0.491	0.000	1.000	0.000	0.719	0.000	1.000	0.000	0.513	0.000
	CR-CNN [57]	0.766	0.224	0.930	0.361	0.783	0.246	0.961	0.392	0.566	0.070	0.967	0.131	0.617	0.112	0.936	0.200	0.683	0.271
	GSR-Net [65]	0.502	0.011	0.994	0.022	0.502	0.011	1.000	0.022	0.515	0.000	1.000	0.000	0.505	0.008	0.998	0.014	0.506	0.019
	CAT-Net [22]	0.630	0.328	0.762	0.459	0.849	0.373	0.782	0.505	0.572	0.093	0.902	0.169	0.721	0.132	0.872	0.229	0.693	0.157
	FCN+DA [6]	0.796	0.844	0.717	**0.775**	0.762	0.322	0.950	0.481	0.541	0.100	0.900	0.180	**0.746**	0.100	0.981	0.182	0.711	0.404
Weak	MIL-FCN [37]	0.647	0.538	0.569	0.553	0.807	0.220	0.732	0.338	0.542	0.062	0.793	0.115	0.578	0.116	0.886	0.205	0.644	0.303
	MIL-FCN [37] + WSCL	**0.829**	0.795	0.690	0.738	**0.920**	0.519	0.983	**0.680**	0.584	0.440	0.714	**0.544**	0.733	0.221	0.966	**0.360**	**0.766**	**0.580**
	Araslanov and Roth [1]	0.642	0.458	0.542	0.496	0.773	0.127	0.902	0.223	0.560	0.077	0.746	0.140	0.665	0.126	0.832	0.219	0.660	0.270
	Araslanov and Roth [1] + WSCL	0.796	0.638	0.726	0.679	0.917	0.324	0.948	0.483	**0.591**	0.220	0.838	0.348	0.701	0.193	0.872	0.316	0.751	0.456

Novel manipulation detection

- Our weakly-supervised method can leverage weakly-annotated images for training
- After finetuning, our method outperforms fully-supervised counterparts

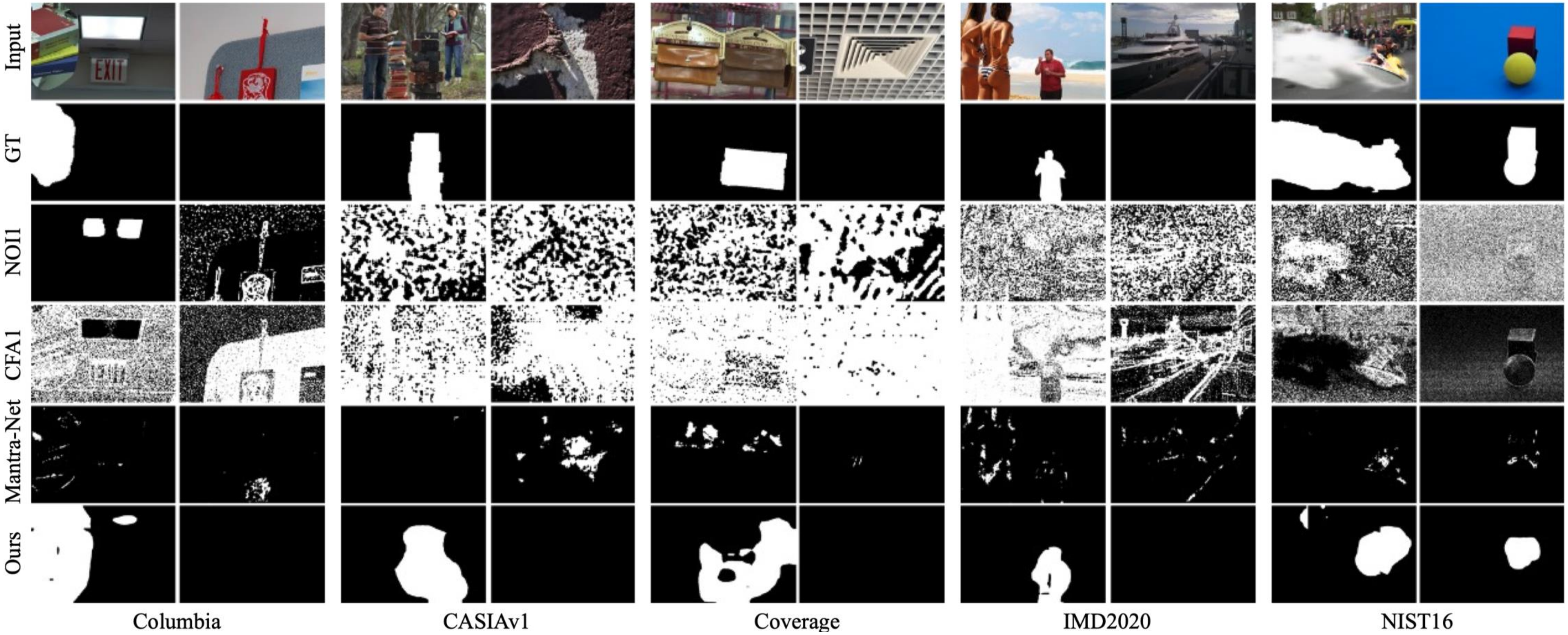
	Method	GIER [43]		IEdit [45]		Avg	
		AUC	F1	AUC	F1	AUC	I-F1
Full	CAT-Net [22]	0.508	0.336	0.532	0.476	0.502	0.406
Full	FCN+DA [6]	0.507	0.428	0.539	0.489	0.523	0.458
Full	MVSS-Net [6]	0.510	0.325	0.537	0.522	0.523	0.423
Weak	MIL-FCN [37] + WSCL	0.574	0.320	0.563	0.556	0.568	0.438
Weak	MIL-FCN [37] + WSCL w/ fine-tune	**0.621**	**0.533**	**0.617**	**0.602**	**0.619**	**0.568**

Pixel-level manipulation localization

- Reasonable pixel-level manipulation localization ability

	Method	Pixel-Level F1						Combined F1				
		CASIAv1	Columbia	Coverage	IMD2020	NIST16	Avg	CASIAv1	Columbia	Coverage	IMD2020	Avg
Un.	NOI1 [29]	0.157	0.311	0.205	0.124	0.089	0.190	0.000	0.000	0.000	0.000	0.000
	CFA1 [13]	0.140	0.320	0.188	0.111	0.106	0.188	0.000	0.000	0.000	0.000	0.000
Full	Mantra-Net [55]	0.155	0.364	0.286	0.122	0.000	0.185	0.000	0.000	0.000	0.000	0.000
	CR-CNN [57]	0.405	0.436	0.291	-	0.238	-	0.382	0.413	0.181	-	-
	GSR-Net [65]	0.387	0.613	0.285	0.175	0.283	0.349	0.042	0.042	0.000	0.026	0.028
	CAT-Net [22]	0.276	0.352	0.134	0.102	0.138	0.200	0.345	0.406	0.149	0.144	0.261
	FCN+DA [6]	0.441	0.223	0.199	0.270	0.167	0.260	0.562	0.305	0.189	0.217	0.318
Weak	MIL-FCN [37]	0.117	0.089	0.121	0.097	0.024	0.090	0.193	0.141	0.118	0.131	0.146
	MIL-FCN [37] + WSCL	0.172	0.270	0.178	0.193	0.110	0.185	0.280	0.386	0.268	0.252	0.296
	Araslanov and Roth [1]	0.112	0.102	0.127	0.094	0.026	0.092	0.182	0.140	0.133	0.046	0.125
	Araslanov and Roth [1] + WSCL	0.153	0.362	0.201	0.173	0.099	0.198	0.250	0.414	0.255	0.159	0.270

Pixel-level manipulation localization



Contributions

- Propose the weakly-supervised image manipulation detection (W-IMD) task to adapt to new mask-free image editing techniques
- Propose weakly-supervised self-consistency learning (WSCL) for W-IMD, and it learns global multi-source information to detect the manipulation
- Strong image-level detection results, and reasonable localization

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