Supplementary Materials of Multi-view Feature Extraction via Tunable Prompts is Enough for Image Manipulation Localization

Table 1: Detailed information about the training and test datasets we used. We use cpmv, spl, and imp to represent the Copy-Move, Splicing, and Inpainting manipulation techniques, respectively. '-' indicates that the data is not available.

Dataset	Fake	Authentic	cpmv	spl	inp
Training					
CASIA2[1]	7,491	5,063	3,235	1,828	0
Testing					
CASIA1[1]	800	920	459	461	0
COVER[10]	100	100	100	0	0
Columbia[5]	183	180	0	180	0
NIST16[2]	0	564	68	288	208
IMD20[7]	414	2,010	-	-	-
DEF-12K[4]	6,000	6,000	2,000	2,000	2,000

1 Details of Training and Test Datasets

We solely utilize CASIA2 [1] to train Prompt-IML. 6 public test datasets are utilized for evaluation, including CASIA1 [1], NIST16 [2], COVERAGE [10], Columbia [5], IMD2020 [7], and DEFACTO [4]. The detailed information for each dataset can be found in Tab.1.

2 Evaluation through AUC Metric

AUC is another commonly used evaluation metric for IML task. To comprehensively assess our model's performance, we report the AUC scores of our model on 5 test datasets in Tab.2. The missing information in the table is due to differences in experimental protocols. Our approach exhibits superior performance across 5 datasets, with an average improvement of 2.8% over IML-ViT.

Table 2: Image Manipulation Localization Performance (AUC score). We highlight the best results in each column in bold. '-' indicates that the data is not available due to the different experimental protocols.

Method	CASIA1	Columbia	NIST16	COVER	IMD20	Average
ObjectFormer[9], CVPR22	0.882	-	-	-	-	-
CFL-Net[6], WACV23	0.863	-	0.799	-	-	-
SAFL-Net[8], ICCV23	0.908	-	-	-	-	-
IML-ViT[3], AAAI24	0.931	0.962	0.818	**0.918**	0.892	0.904
Prompt-IML	**0.954**	**0.978**	**0.891**	0.913	**0.923**	**0.932**

3 Ablation Study of Prompts

We first explore the impact of tunable prompts quantity on model performance. Specifically, we set the number of prompts to 5, 10, 20, and 30, and report the F1 scores of each setting on 6 test datasets in the top part of Tab.3. Due to the minor performance differences, we use 5 as the default number of prompts, as this setting is more resource-efficient in computing self-attention. Then, we explore the impact of shallow prompt and deep prompt. In the shallow prompt experiment, we use fully connected layers to adjust the dimensions C_i of the prompts between the backbone's layers to meet the size requirements. We report the F1 scores in the bottom part of Tab.3 and choose the deep prompt strategy due to the experiments' results.

Table 3: Ablation study of prompts. The upper part shows the impact of the number of prompts, while the lower part demonstrates the differences between shallow prompt and deep prompt. We highlight the best results in each column in bold.

	CASIA1	Columbia	NIST16	COVER	DEF-12K	IMD20
5	0.686	0.882	0.415	**0.429**	**0.237**	**0.471**
10	**0.713**	**0.906**	0.410	0.404	0.233	0.456
20	0.691	0.880	0.399	0.392	**0.237**	0.435
30	0.701	0.903	**0.416**	0.412	0.229	0.459
shallow prompt	0.684	**0.896**	0.373	0.350	0.219	0.402
deep prompt	**0.686**	0.882	**0.415**	**0.429**	**0.237**	**0.471**

4 Additional Localization Results

To fully showcase the outstanding performance of our method, we present additional results in Fig. 1. The tampered images are sourced from 5 different test datasets, with significant variations in the size of the manipulated areas. Experimental results demonstrate the superior generalization capability of our model.

References

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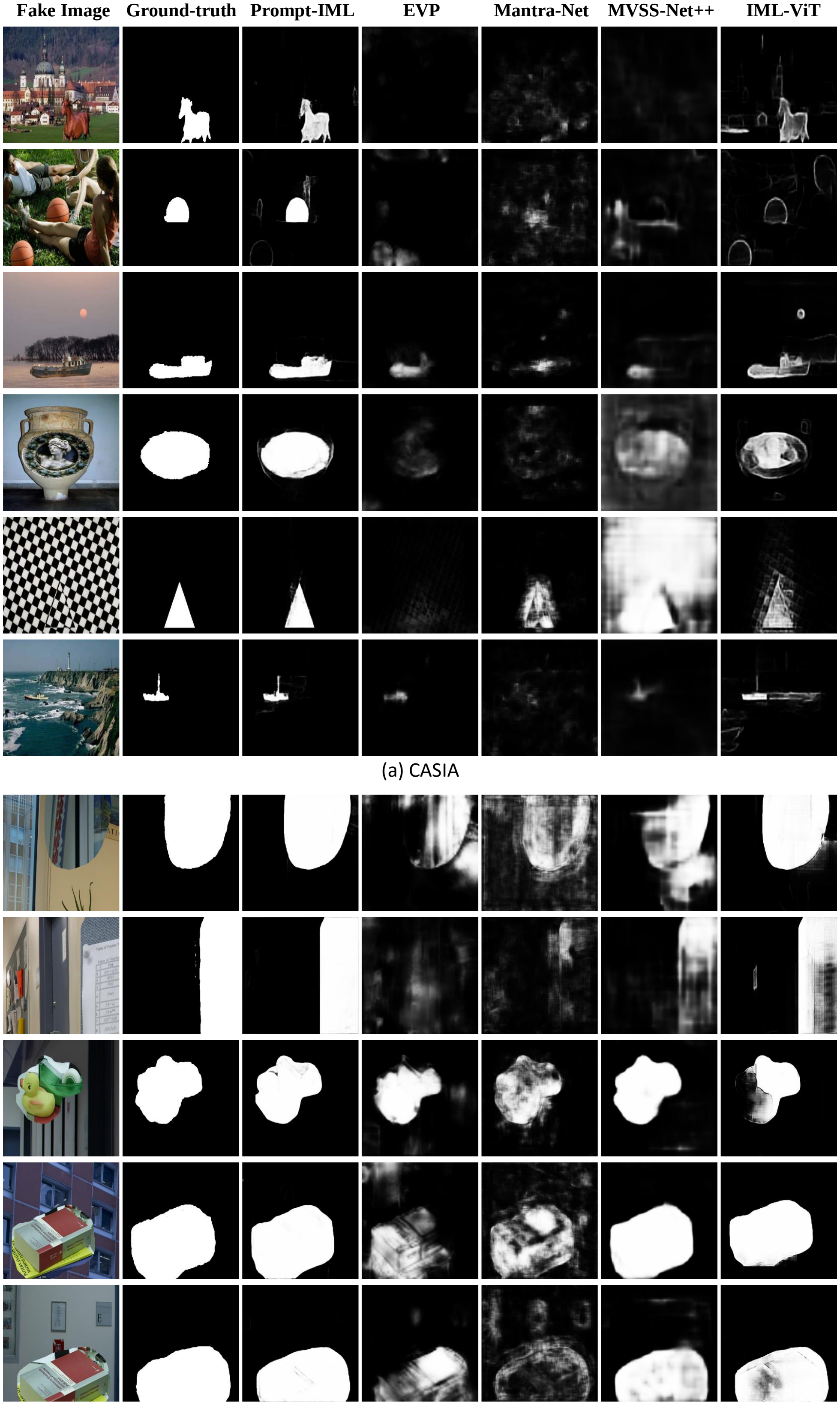
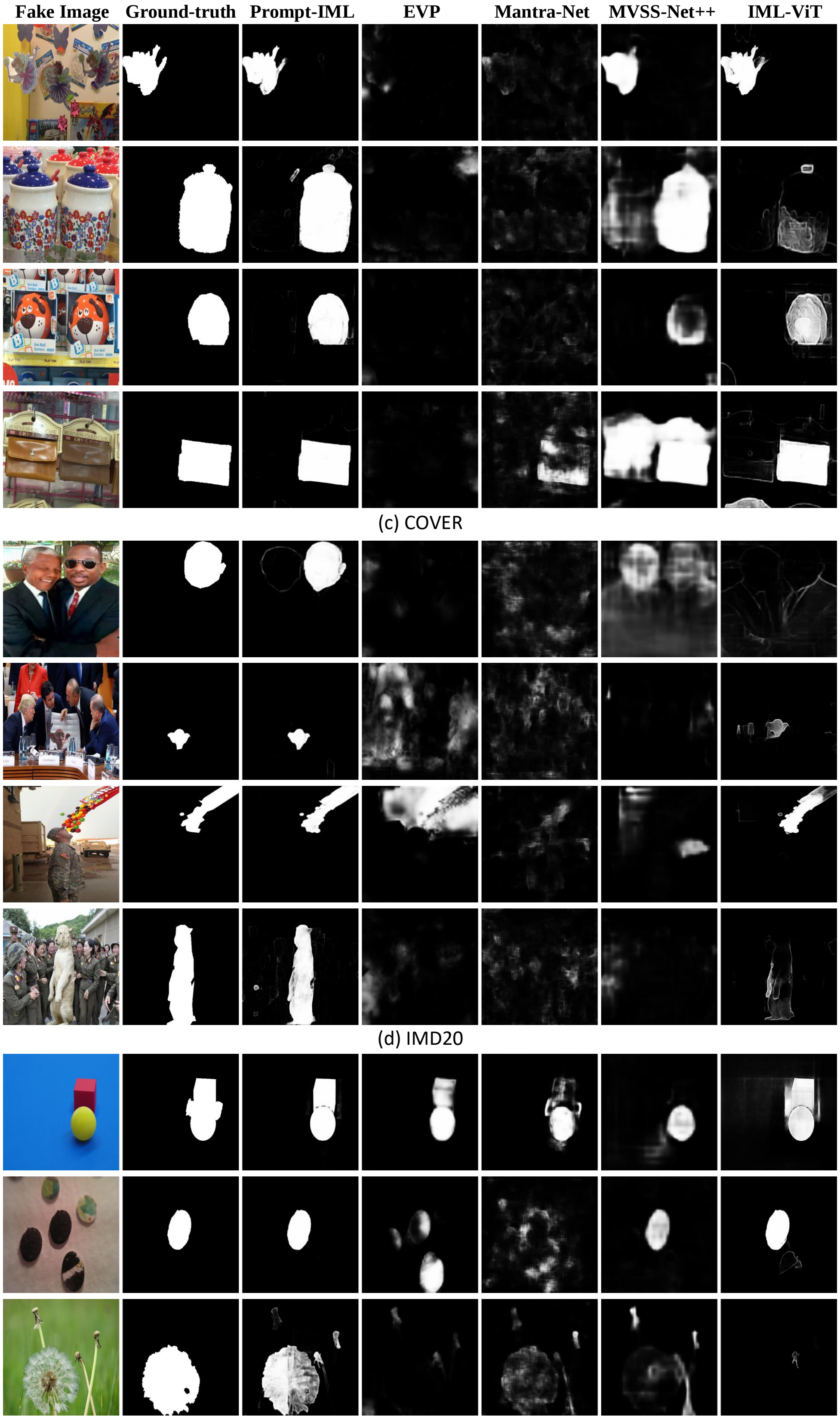


(a) CASIA

(b) Columbia



(c) COVER

(d) IMD20

(e) NIST16

Figure 1: Additional manipulation localization results on images originating from 5 datasets. Columns from left to right are: fake image, ground-truth, Prompt-IML, EVP, Mantra-Net, MVSS-Net++ and IML-ViT.