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• **Supplementary File** •

Mobile person re-identification with a lightweight trident CNN

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Appendix A The Quantitative Results and Explanations

In this supplementary file, we have illustrated the quantitative results and explanations for the proposed methods.

We have conducted experiments on the public datasets (Market-1501 [2] and VIPeR [15]) for person re-ID. Firstly, the proposed method is pre-trained on the DukeMTMC-reID [16] dataset. Then, the fine-tuning operation is performed on the Market-1501 and VIPeR datasets. The improved performance on the two public datasets are shown in Table A1 A2, which show that our methods have gotten a better performance comparing with most of the latest algorithms. The related methods are listed in the references.

Table A1 Results on the Market-1501 dataset.

Method	Ref	Rank=1	MAP
LOMO+XQDA [1]	ICCV 2015	43.37	22.22
Zheng et al. [2]	ICCV 2015	34.40	14.09
PersonNet [3]	CVPR 2016	37.21	18.57
Hybrid [4]	PR 2016	48.15	29.94
End-2-End CAN [5]	TIP 2017	48.24	24.43
CycleGAN (basel.) [6]	ICCV 2017	45.60	19.10
MVLDML+ [7]	TIP 2019	58.22	33.70
T-net [8]	PRL 2019	65.02	50.71
Ours		**67.24**	**57.20**

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Table A2 Results on the VIPeR dataset.

Method	Ref	Rank=1	Rank=10	Rank=20
LOMO+XQDA [1]	ICCV 2015	40.00	80.51	91.10
DeepFeature. [9]	PR 2015	40.50	70.40	89.26
DeepList [10]	TCSVT 2016	40.51	81.04	91.07
IEIT [11]	IJCB 2017	50.40	85.80	-
PDC [12]	ICCV 2017	51.27	84.18	91.46
MLS [6]	CVPR 2018	50.10	84.35	-
EB-bias [14]	CVPR 2018	51.90	84.80	90.02
MVLDML+ [7]	TIP 2019	50.00	88.55	94.70
Ours		**51.31**	**88.58**	**95.41**

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