Supplementary Materials: An Empirical Study of Adder Neural Networks for Object Detection

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A Quantization

As discussed in prior literature [1, 4], one operation of floating-point addition and multiplication have energy costs of 0.9 pJ and 3.7 pJ, respectively. Meanwhile, one operation of 8-bit integer addition and multiplication have 0.03 pJ and 0.2 pJ energy costs, demonstrating much lower cost than floating-point operation. Therefore, it is important to explore whether adder detectors performs well for INT8 quantization. We tried to adopt INT8 post quantization for our Adder FCOS (B+N) model, which suffers 0.8 mAP drop compared with full precision model, as shown in Table A. The energy reduction further increases from 29% to 35%. Note that post training quantization is not optimal for INT8 models, and quantization-aware training may greatly further improve the accuracy.

Table A: Quantitative results of INT8 convolutional and adder models

	#MUL	#ADD	FP32		INT8	
			Energy	mAP	Energy	mAP
FCOS	214.7	214.7	987.62	38.4	49.38	38.1
Adder FCOS (B+N)	112.9	316.5	702.58 (0.71×)	37.0 (-1.4)	32.08 (0.65×)	36.2(-1.9)

B Training Tricks for CNN-based Detectors

The training tricks in Table 1 in the main body of this paper mainly include well-tuned learning rate with cosine decay. We also tried to utilize these tricks for training CNN-based object detectors. As shown in Table B, these tricks bring 0.2%-0.6% mAP gain for various CNN-based detectors. On contrast, this strategy improves the adder detector for 1.2% mAP, which indicates that the well-developed hyper-parameters for CNN-based detectors are often not optimal for adder detectors.

Table B: Comparing CNN-based detectors and adder detectors for learning rate strategy.

Model	Step LR	Cosine LR + LR tuning
RetinaNet	36.4	36.6 (+0.2)
FCOS	38.4	39.0 (+0.6)
Adder FCOS	33.2	34.8 (+1.2)

C Robustness to Domain Shift

It is an interesting topic to explore the robustness to the domain shift for AdderNet-based detector. We utilize the FCOS models trained on COCO to evaluate on the Cityscapes dataset for the common

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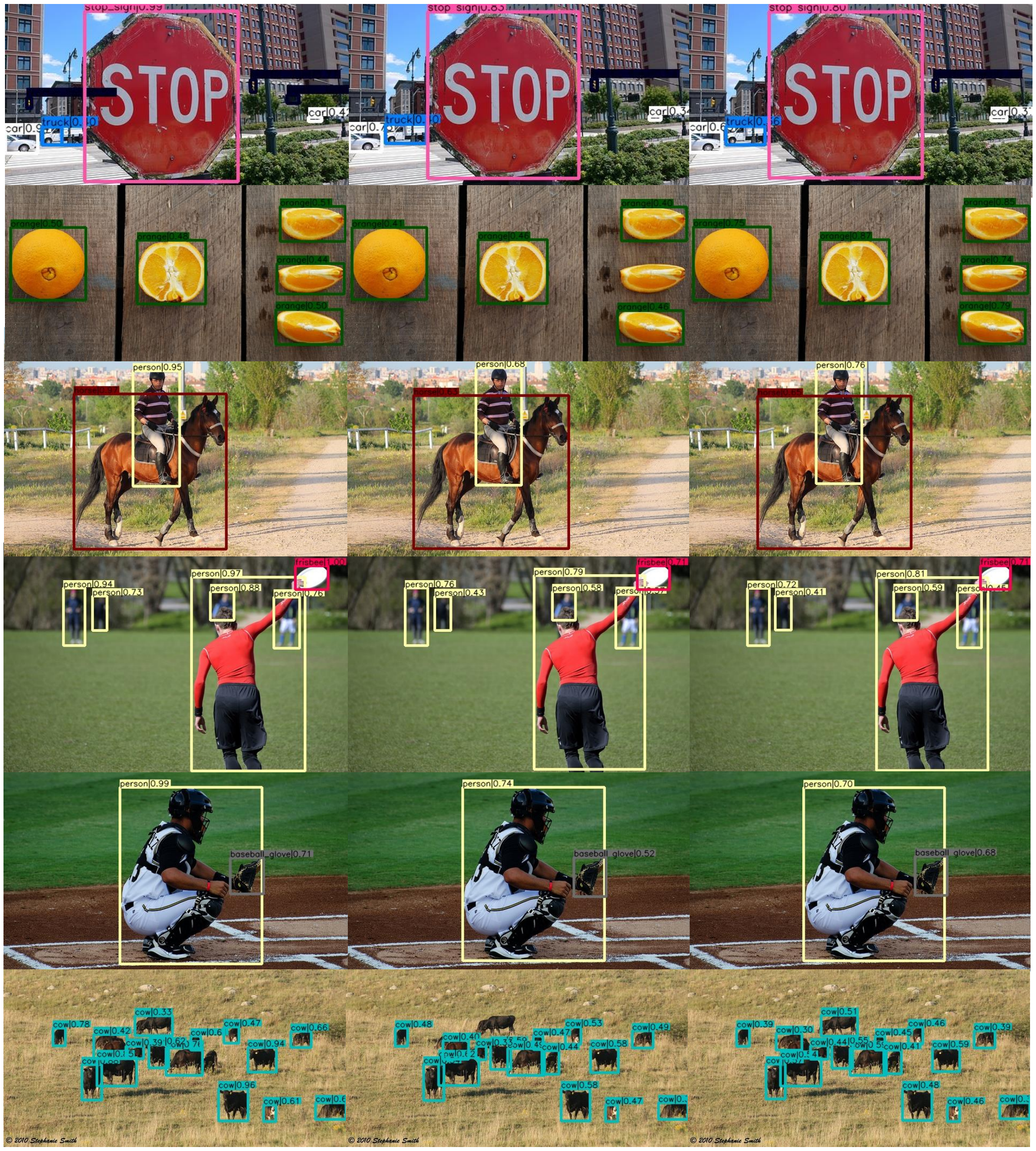

(a) RetinaNet (b) FCOS (c) Adder FCOS (Ours)

Figure 1: Qualitative results of RetinaNet [2], FCOS [3] and our proposed Adder FCOS.

object categories without fine-tuning. More specifically, we adopt the coco-trained models to predict the detection results for Cityscapes val set, and map the original ground-truth categories of Cityscapes to COCO (80 classes) to calculate the mAP. As shown in Table C, Adder FCOS suffers from 2.2% mAP drop on Cityscapes compared with convolutional counterpart, which is similar with the performance drop on COCO. This demonstrates that adder detectors have similar robustness performance to the domain shift with CNN detectors.

Table C: Robustness to the domain shift for AdderNet-based and CNN-based detectors.

Model	COCO mAP	Cityscapes mAP
FCOS	38.4	29.4
Adder FCOS (B+N)	36.5 (-1.9)	27.2 (-2.2)

D Visualization

Figure 1 shows more qualitative results of our proposed adder detection and state-of-the-arts detectors, including RetinaNet [2] and FCOS [3]. Adder FCOS works well for a variety of challenging scenarios and has similar predictions with other detectors. Qualitative results for RetinaNet-MS-600 and its adder variants are shown in Figure 2.

References

[1] William Dally. High-performance hardware for machine learning. *NIPS Tutorial*, 2, 2015.

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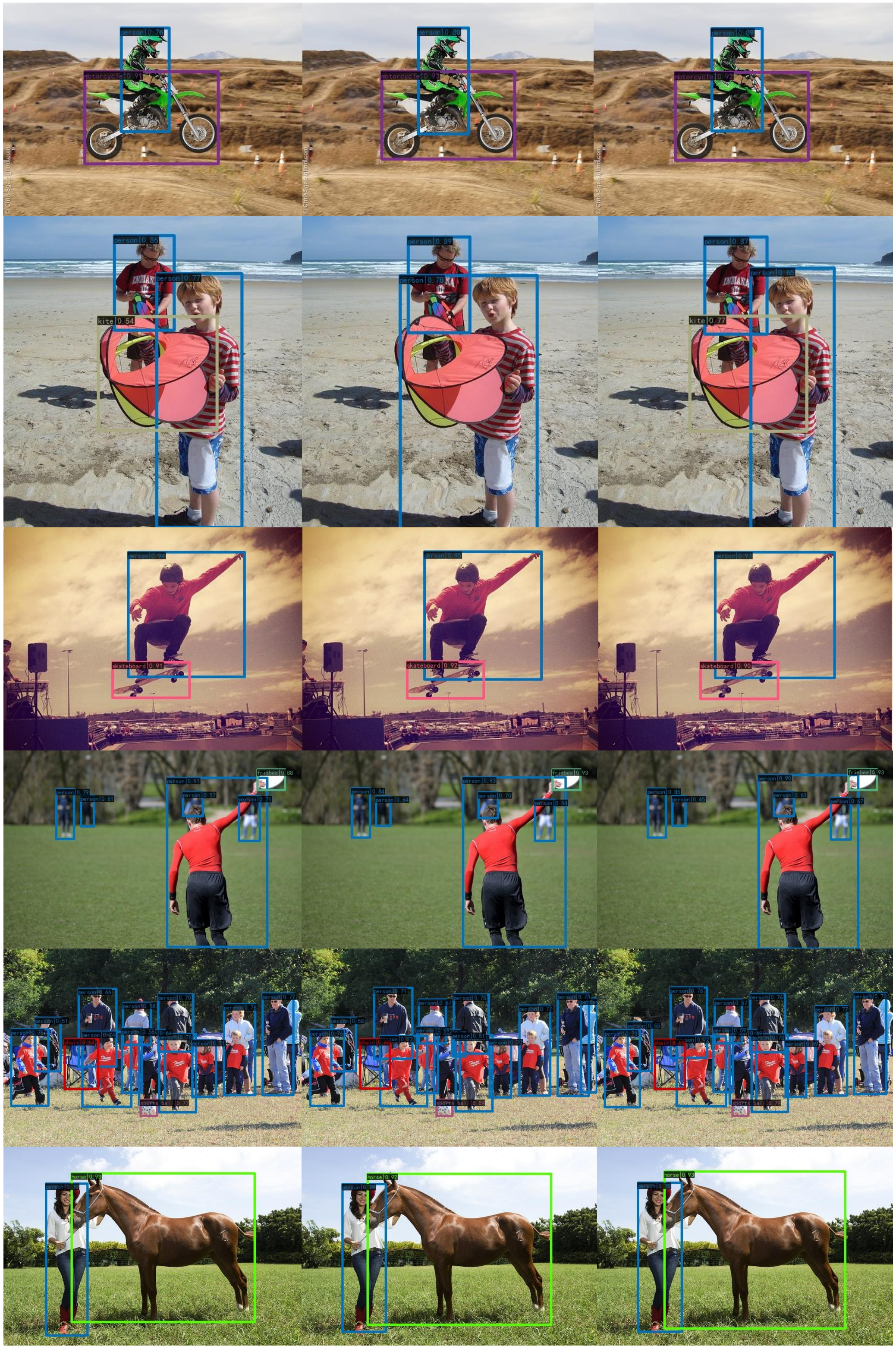
Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] See Section 5.
   (c) Did you discuss any potential negative societal impacts of your work? [N/A]
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
   (b) Did you include complete proofs of all theoretical results? [N/A]
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [No]
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] See Section 4.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [N/A]
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes]
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes]
   (b) Did you mention the license of the assets? [N/A]
   (c) Did you include any new assets either in the supplemental material or as a URL? [N/A]
   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [N/A]
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [N/A]
5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]



(a) RetinaNet-MS-640 (b) Adder RetinaNet-MS-640 (B+N) (c) Adder RetinaNet-MS-640 (B+N+H)

Figure 2: Qualitative results of RetinaNet-MS-640 [2] and our proposed adder detectors.