

適合邊緣佈署之類神經網路研發與應用*

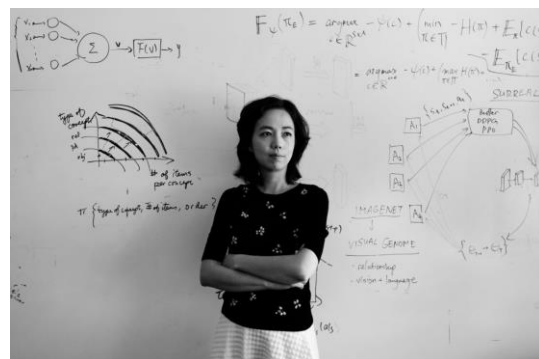
林永隆

創鑫智慧股份有限公司

*Work done with students in National Tsing Hua University

Partially supported by a grant from the Ministry of Science and Technology

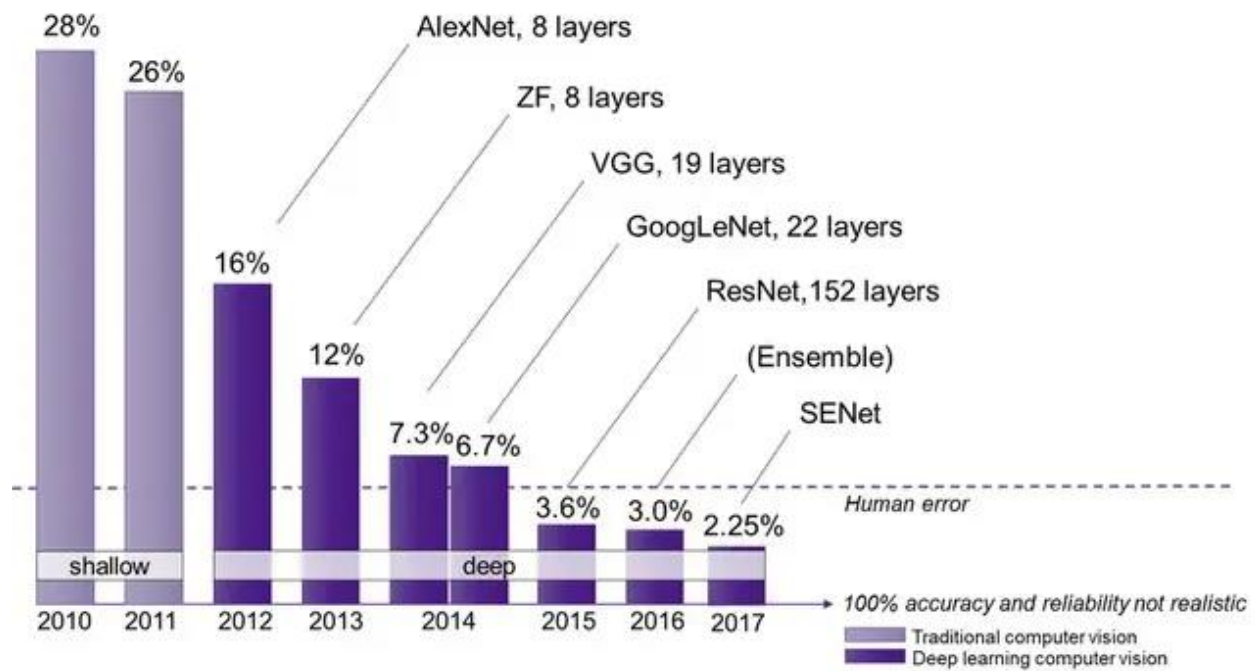
A Grand Challenge -- ImageNet Image Classification



IMAGENET

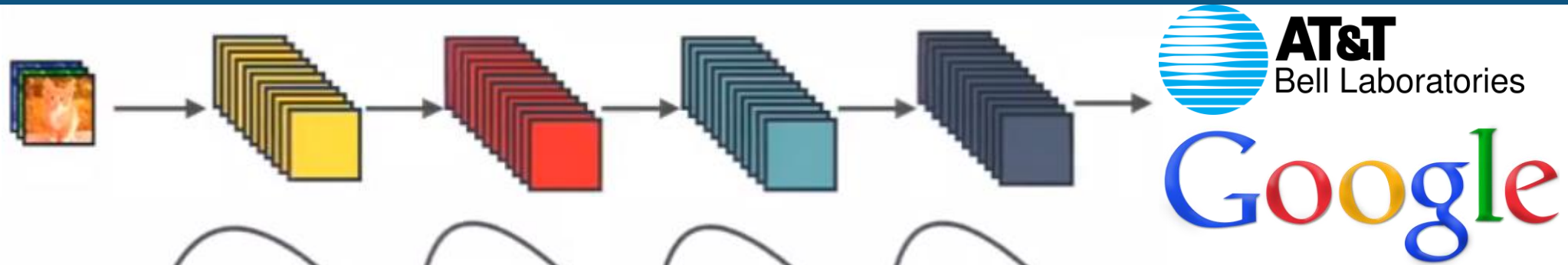
- 1,000 object classes (categories).
- Images:
 - 1.2 M train
 - 100k test.

| | | | |
|-------------|--------------------|-----------------------|-----------------|
| | | | |
| mite | container ship | motor scooter | leopard |
| black widow | lifeboat | go-kart | leopard |
| cockroach | amphibian | moped | cheetah |
| tick | fireboat | bumper car | snow leopard |
| starfish | drilling platform | golfcart | Egyptian cat |
| | | | |
| grille | mushroom | cherry | Madagascar cat |
| convertible | agaric | dalmatian | squirrel monkey |
| grille | mushroom | grape | spider monkey |
| pickup | jelly fungus | elderberry | titi |
| beach wagon | gill fungus | fordshire bullterrier | Indri |
| fire engine | dead-man's-fingers | currant | howler monkey |

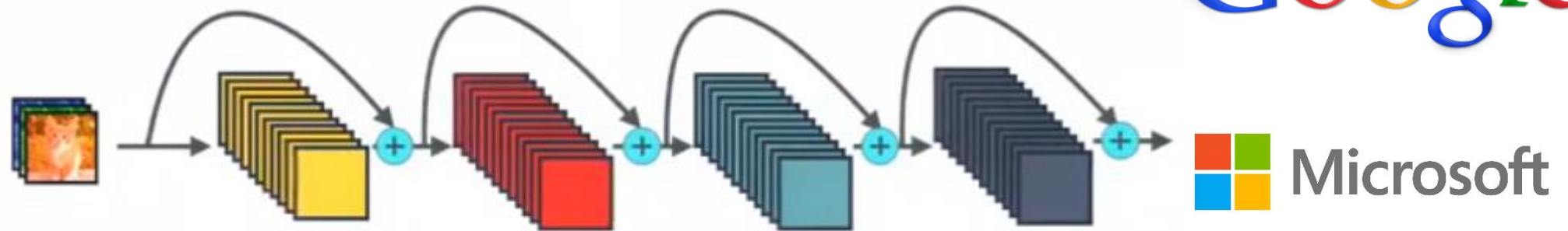


CNN Evolution – The more shortcuts, the better?

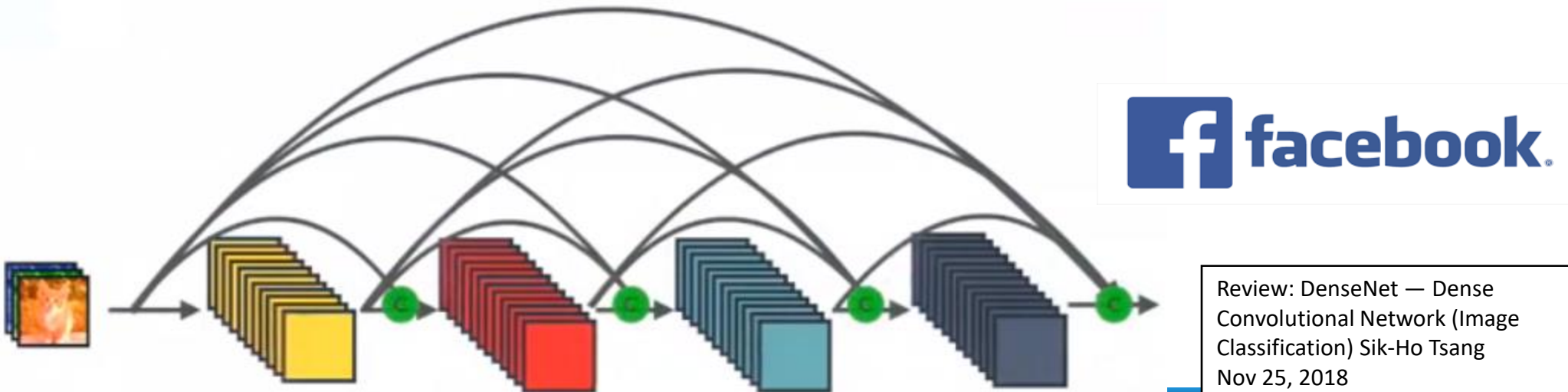
1998 LeNet
2012 AlexNet
2014 VGG
2014 GoogLeNet



2015 ResNet



2018 DenseNet



CNN Architecture Design Considerations

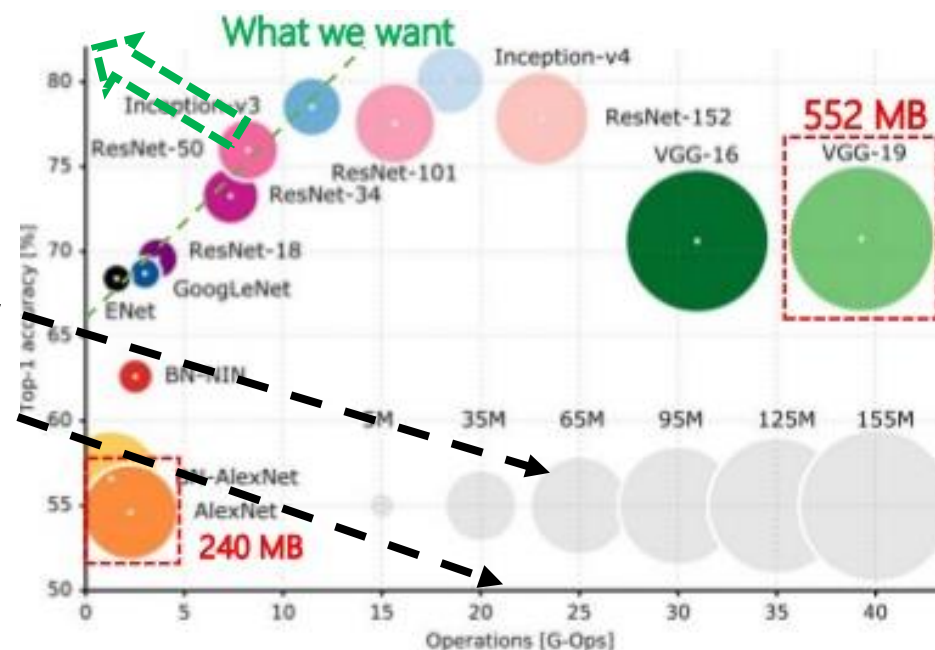
Conventional Metrics

- Accuracy
- Model size (# Parameters)
- Operations per inference

What we really care

- Accuracy, of course!
- Inference time (~ #Ops?)
- Energy consumption (~ #Ops?)
- Model Size
- General applicability
- Trainability, Robustness, etc

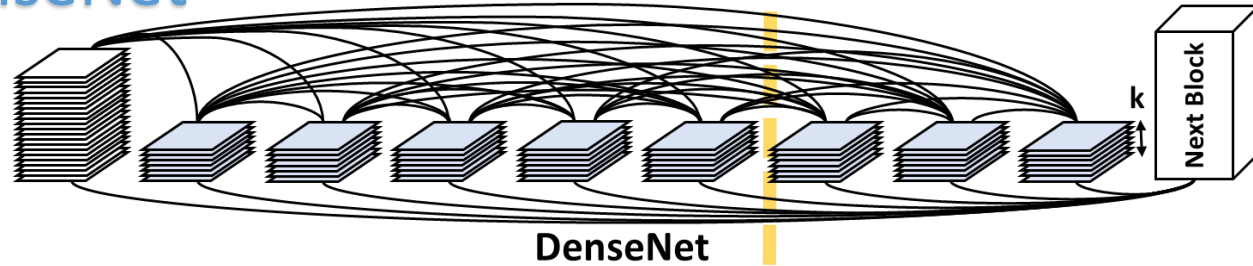
ImageNet Classification Challenge



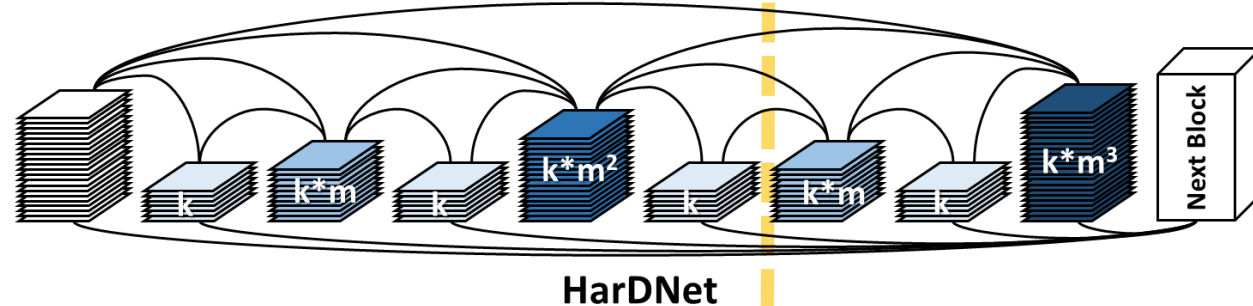
Canziani, Alfredo, Adam Paszke, and Eugenio Culurciello. "An analysis of deep neural network models for practical applications." arXiv preprint arXiv:1605.07678 (2016).

HarDNet – Harmonic Densely Connected CNN

2018 DenseNet



2019 HarDNet



1. Harmonic Wave

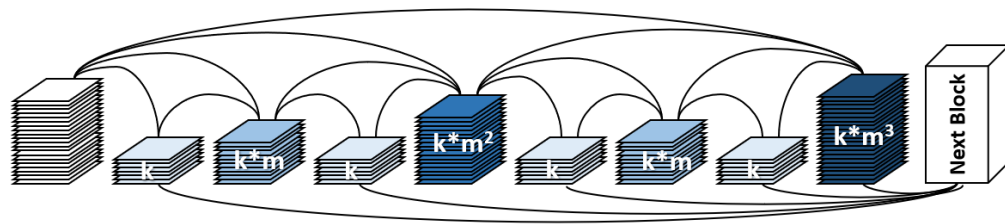


國立清華大學
NATIONAL TSING HUA UNIVERSITY

3. Variable Channels

2. Less Intermediate Result

HarDNet: A Low Memory Traffic Network



An 8-Layer HarDBlk
Similarly, 4-Layer, 16-Layer

| SSD512 Resolution | ImageNet Resolution | HarDNet 68 | HarDNet 85 |
|-------------------|---------------------|--|--|
| 512x512 | 224x224 | 3x3 32 stride=2 | 3x3 48 stride=2 |
| 256x256 | 112x112 | 3x3 64 | 3x3 96 |
| 128x128 | 56x56 | HarDBlk 8 Layers, k=14 1x1 128 | HarDBlk 8 Layers, k=24 1x1 192 |
| 64x64 | 28x28 | HarDBlk 16 Layers, k=16 1x1 256 | HarDBlk 16 Layers, k=24 1x1 256 |
| | | HarDBlk 16 Layers, k=20 1x1 320 | HarDBlk 16 Layers, k=28 1x1 320 |
| | | HarDBlk 16 Layers, k=40 1x1 640 | HarDBlk 16 Layers, k=48 1x1 720 |
| 32x32 | 14x14 | HarDBlk 4 Layers, k=160 1x1 1024 | HarDBlk 4 Layers, k=256 1x1 1280 |

Enhanced
Local Feature
Extraction

Feedback on HarDNet



ICCV 2019
Seoul, Korea

Conventional Metrics

- Accuracy
- Operations per inference
- Model size (# Parameters)

What we really care

- Accuracy, of course!
- Inference time (~ #Ops?)
- Energy consumption (~ #Ops?)
- Model Size
- General applicability
- Trainability, Robustness, etc

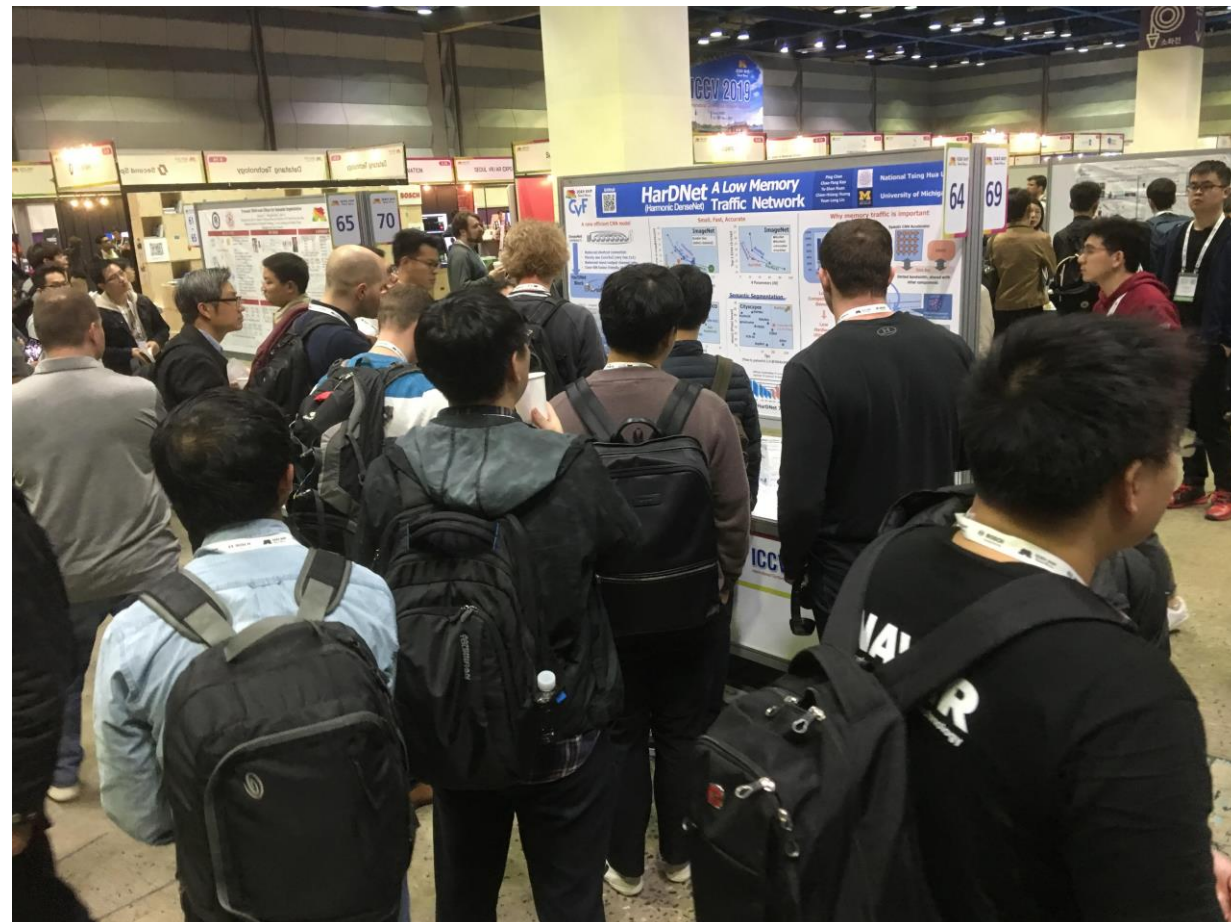
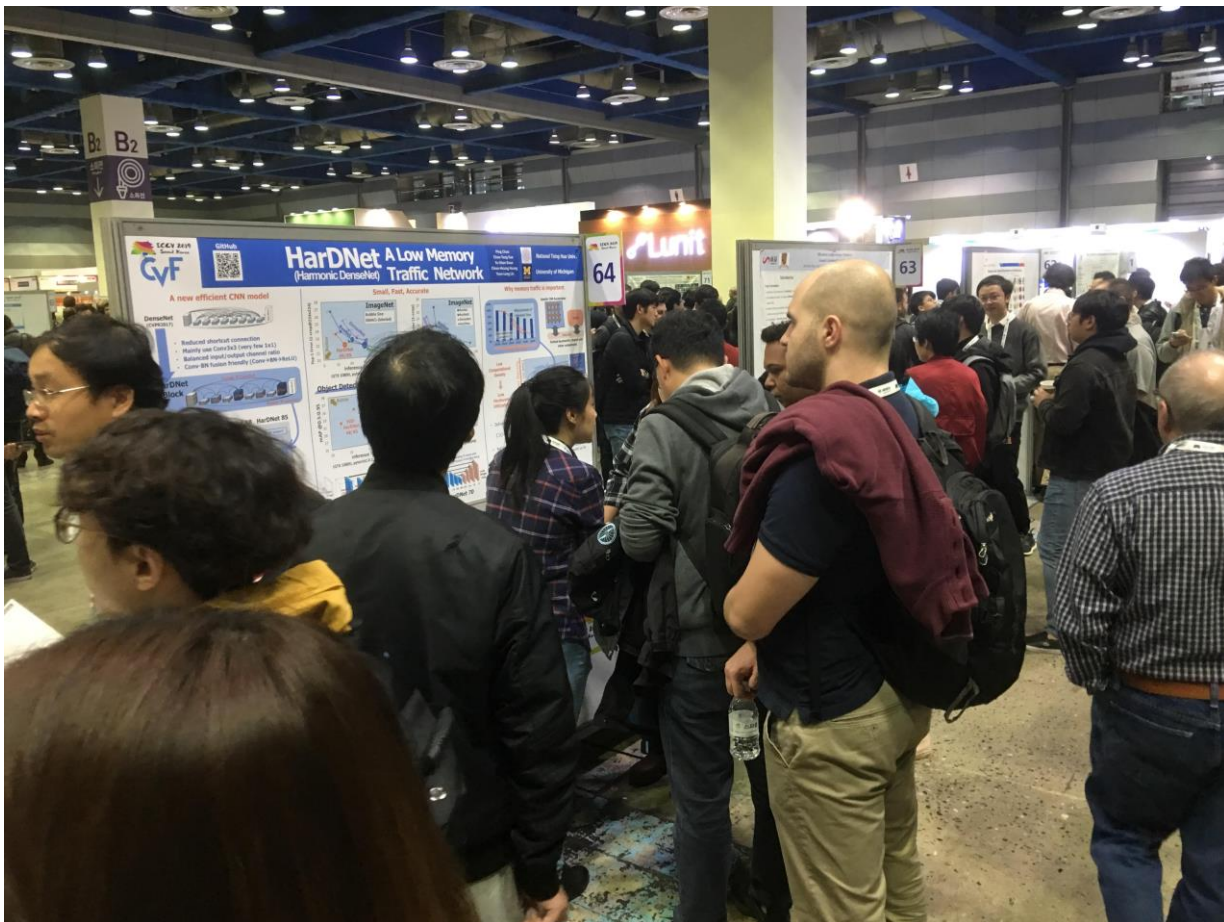
Area Chair Comment:

... This paper makes a meaningful contribution to the literature by introducing a new proxy metric for real-world performance, and additionally showing how neural network architectures might be designed to optimize that metric. This is a fresh idea in a space where nearly every paper focuses exclusively on FLOPs and parameter counts.

HarDNet @ ICCV-2019, Seoul



ICCV 2019
Seoul, Korea



HarDNet Open Source

800+ Stars



✓ GitHub Open Source

- ✓ <https://github.com/PingoLH/Pytorch-HarDNet>
- ✓ [ICCV 2019] HarDNet: A Low Memory Traffic Network

 **Pytorch-HarDNet** Public

35% faster than ResNet: Harmonic DenseNet, A low memory traffic network

 Python  355  61

 **FCHarDNet** Public

Fully Convolutional HarDNet for Segmentation in Pytorch

 Python  171  48


 **CenterNet-HarDNet** Public

Forked from xingyizhou/CenterNet

Object detection achieving 44.3 mAP / 45 fps on COCO dataset

 Python  164  25

✓ In "PapersWithCode"

- ✓ <https://paperswithcode.com/paper/hardnet-a-low-memory-traffic-network> 
- ✓ **State-Of-The-Art for Real-Time Semantic Segmentation on Cityscapes**
- since 2019/09
- ✓ #5 for Real-Time Object Detection on COCO
- ✓ **State-Of-The-Art for Polyp Segmentation on Kvasir**



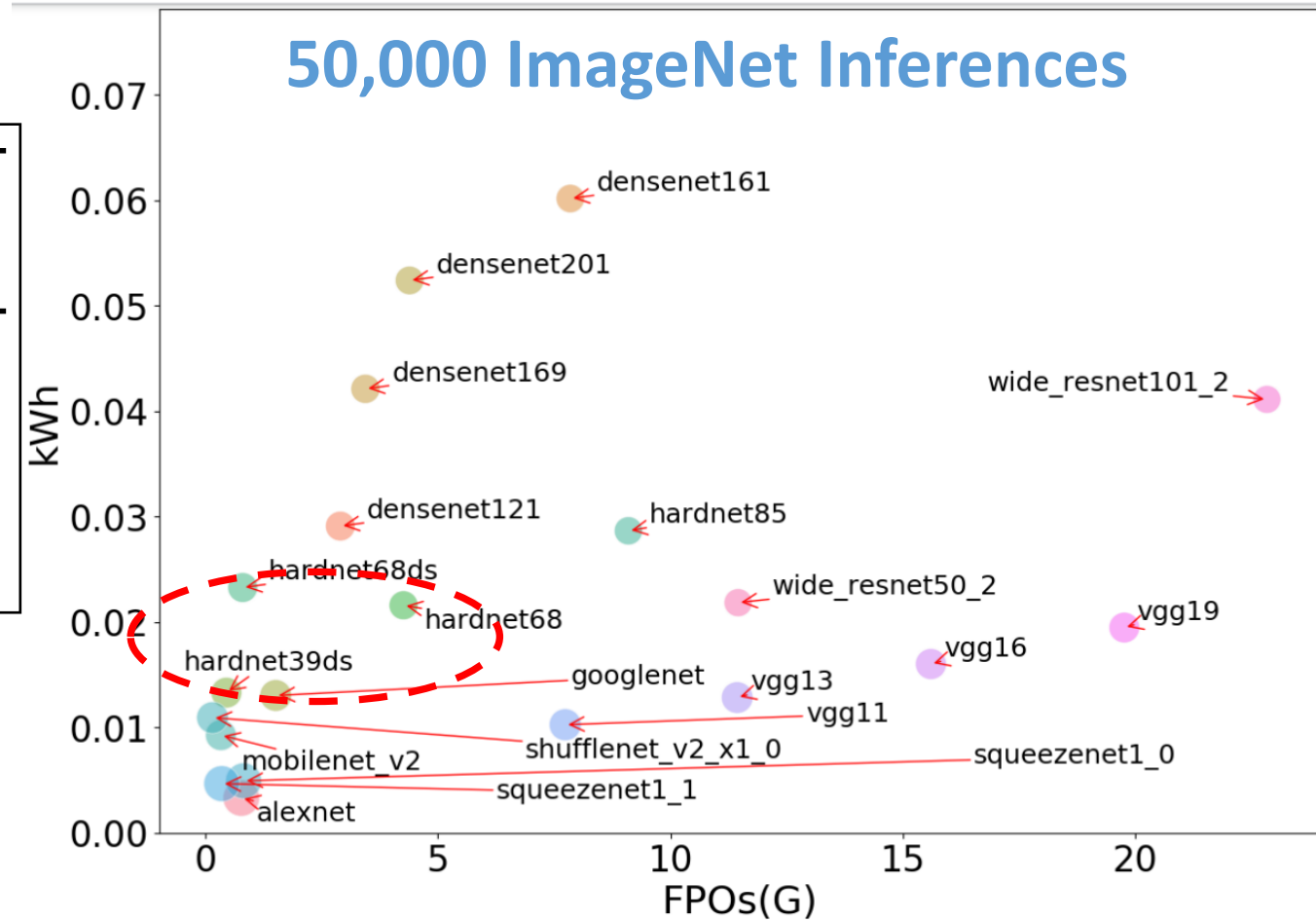
HarDNet is Energy Efficient

TOWARDS THE SYSTEMATIC REPORTING OF THE ENERGY AND CARBON FOOTPRINTS OF MACHINE LEARNING

A WORKING PAPER

Peter Henderson[†], Jieru Hu[‡], Joshua Romoff[◊]
 Emma Brunskill[†], Dan Jurafsky[†], Joelle Pineau^{‡,◊}
[†]Stanford University, [‡]Facebook, [◊]Mila, McGill University

February 14, 2020



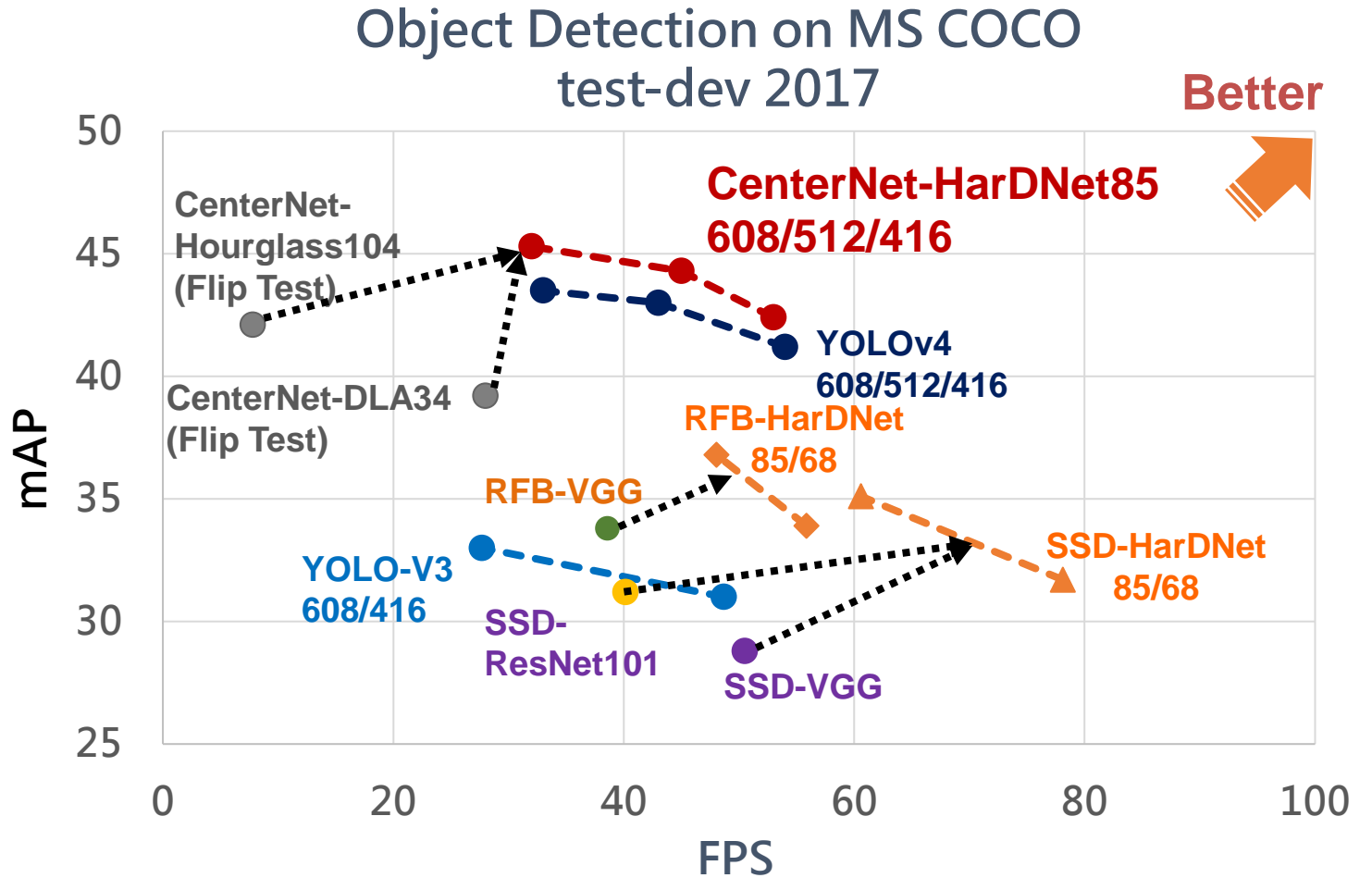
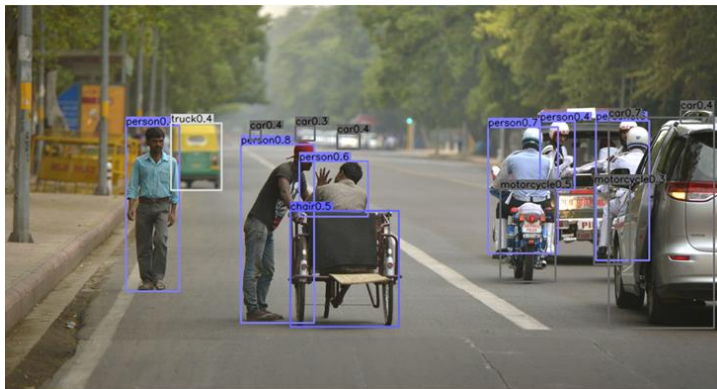
Object Detection

HarDNet Empowers Famous Detectors

SSD-VGG,
SSD-ResNet101 →
SSD-HarDNet

RFB-VGG →
RFB-HarDNet

CenterNet-DLA,
CenterNet-Hourglass →
CenterNet-HarDNet



(Pascal GPU @512*512- FP32) from Paperswithcode

SSD-HarDNet for Warehouse AGVs

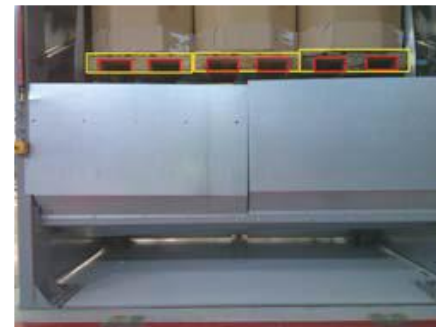


A Comparison of Deep Learning Models for Pallet Detection in Industrial Warehouses



TABLE III
COCO METRICS FOR CNNs DETECTION
OF THE FRONT SIDES OF PALLETS AND PALLET POCKETS.

| | Faster R-CNN | SSD | YOLOv4 |
|----------------------|--------------|------|--------|
| AP | 75.4 | 75.8 | 69.1 |
| AP_{50} | 93.8 | 92.0 | 86.3 |
| AP_{75} | 89.7 | 88.0 | 82.1 |
| AP_S | 0.0 | 6.5 | 14.3 |
| AP_M | 37.7 | 40.5 | 18.3 |
| AP_L | 78.8 | 78.3 | 73.6 |
| AR_{max1} | 12.6 | 12.6 | 11.7 |
| AR_{max10} | 53.3 | 53.6 | 49.4 |
| AR_{max100} | 82.1 | 80.4 | 78.0 |
| AR_S | 0.0 | 6.3 | 18.4 |
| AR_M | 53.4 | 50.9 | 31.1 |
| AR_L | 84.8 | 82.7 | 82.1 |
| Pallet front side AP | 80.1 | 81.5 | 69.5 |
| Pocket AP | 70.8 | 70.1 | 68.7 |



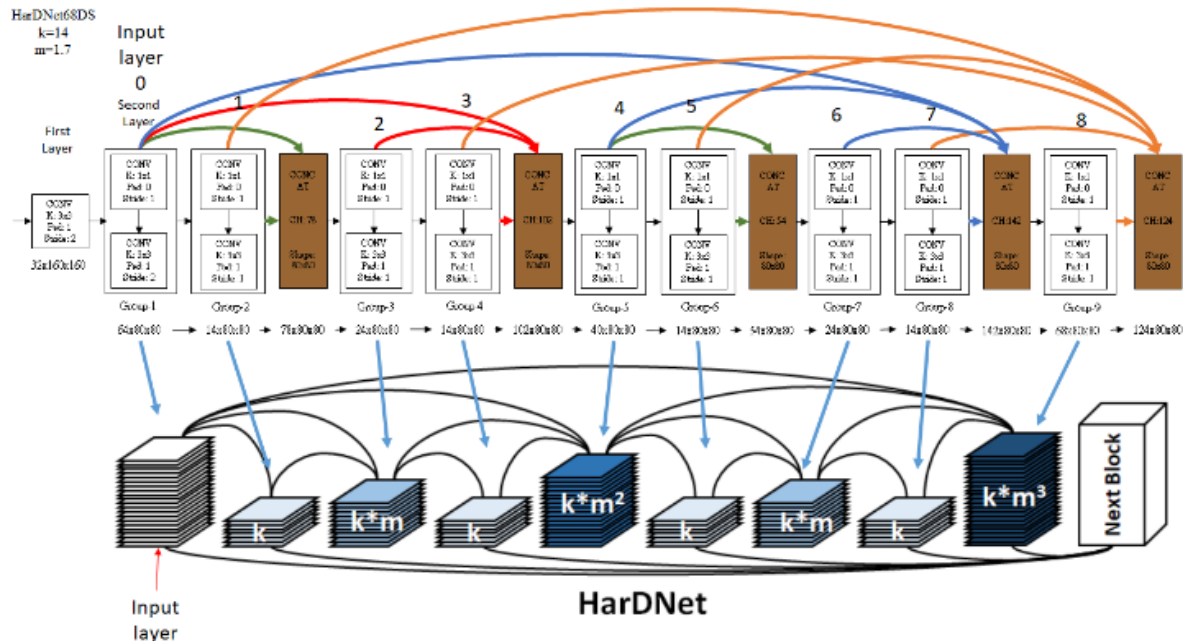
SSD-HarDNet for Road Maintenance Inspection

AI Driven Road Maintenance Inspection

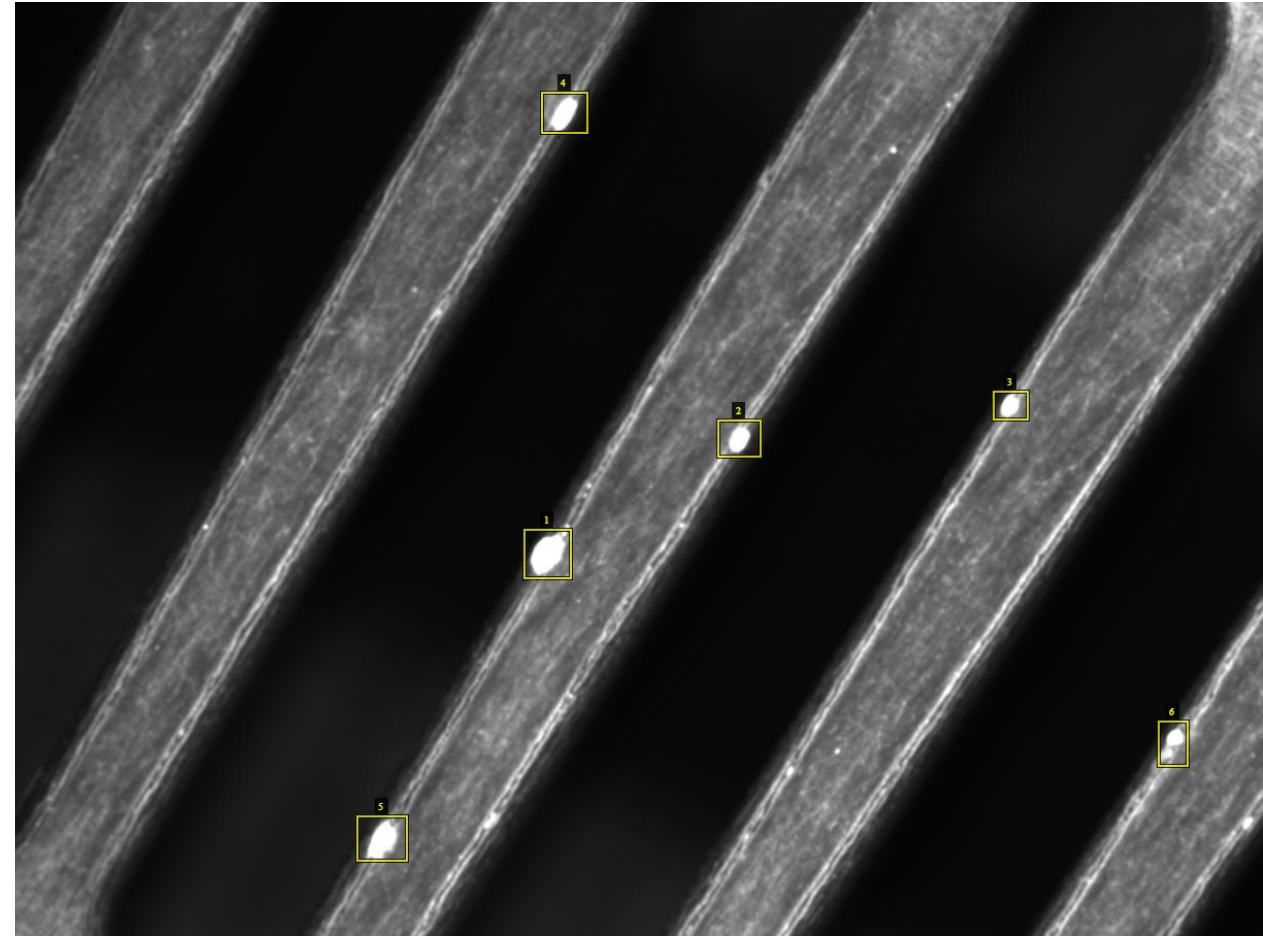
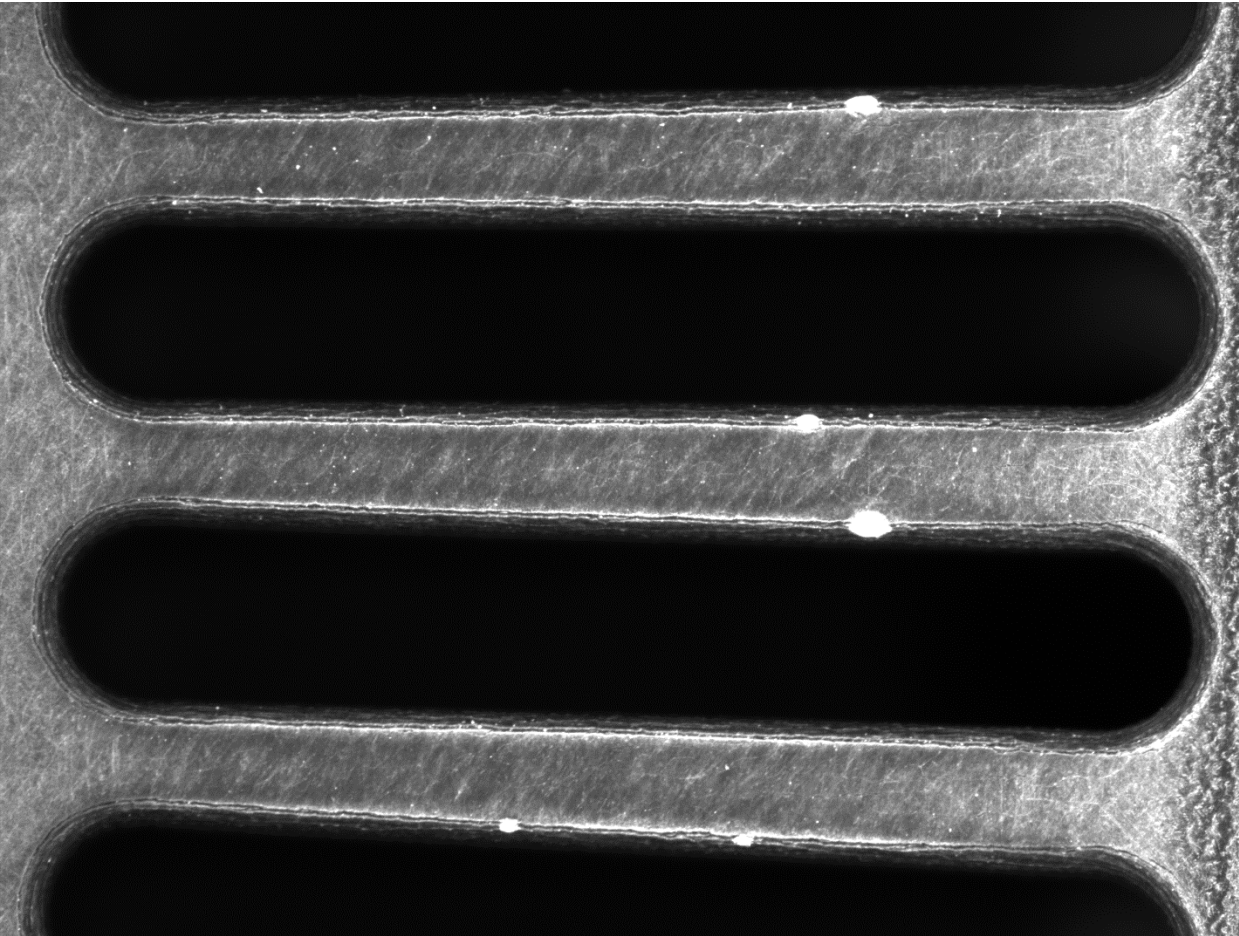


Europe

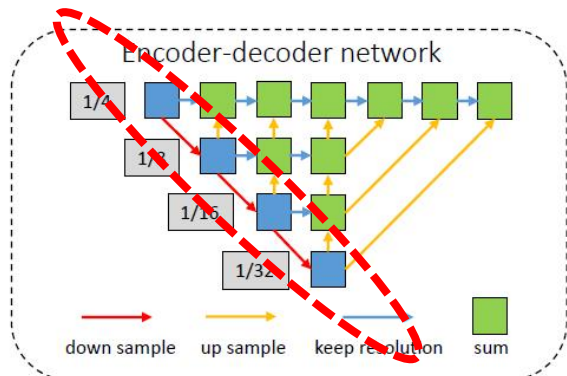
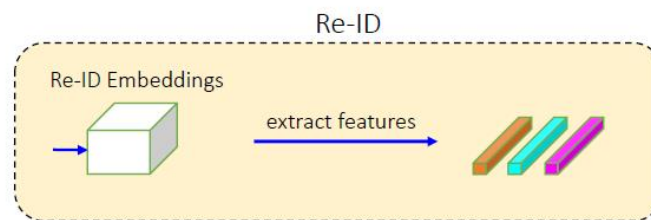
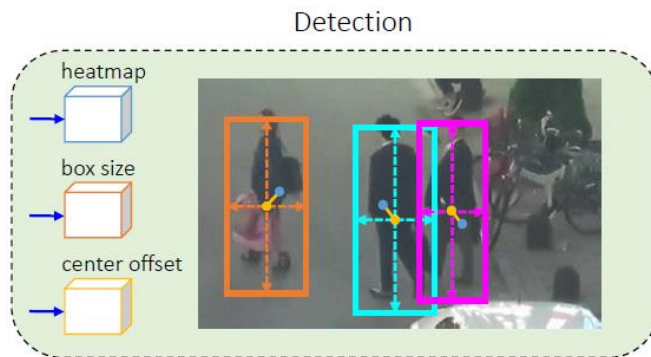
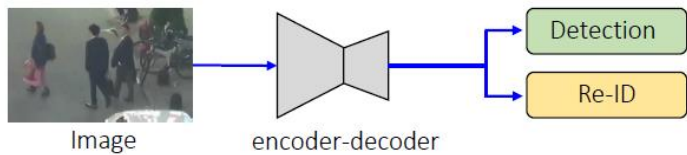
+ In-House RGPNet



CenterNet-HarDNet for Foundry Parts Inspection



HarDNet85 – Best B’bone for SOTA FairMOT



FairMOT: On the Fairness of Detection and Re-Identification in Multiple Object Tracking



| Backbone | w/ MLFF | MOTA↑ | IDF1↑ | IDs↓ | AP↑ | TPR↑ | Acc↑ |
|-------------------|---------|-------------|-------------|------------|-------------|-------------|-------------|
| ResNet-34 | | 63.6 | 67.2 | 435 | 75.1 | 90.9 | 75.2 |
| ResNet-50 | | 63.7 | 67.7 | 501 | 75.5 | 91.9 | 77.8 |
| RegNetY-4.0GF | | 63.9 | 68.0 | 407 | 75.8 | 91.9 | 79.4 |
| ResNet-34-FPN | ✓ | 64.4 | 69.6 | 369 | 77.7 | 94.2 | 75.2 |
| RegNetY-4.0GF-FPN | ✓ | 65.8 | 69.3 | 257 | 78.0 | 94.3 | 79.4 |
| HRNet-W18 | ✓ | 67.4 | 74.3 | 315 | 80.5 | 94.6 | 76.8 |
| DLA-34 | ✓ | 69.1 | 72.8 | 299 | 81.2 | 94.4 | 76.9 |
| HarDNet-85 | ✓ | 71.2 | 74.5 | 198 | 82.6 | 95.8 | 77.0 |



FairMOT + HarDNet for Multiple Vehicle Tracking



多类别车辆跟踪 -- 模型训练、评估、预测、优化到部署的全流程方案

| 模型 | IDF1 | 推理速度- V100 | 推理速度- T4 | 准确率 | 召回率 |
|-------------------------------|------|---------------|-------------|-------------|-------------|
| MCFairMOT +DLA-34 | 46.3 | 14.1 | 11.5 | 74 | 50.9 |
| MCFairMOT +HRNetV2- W18 | 50.5 | 15.8 | 13.6 | 80.2 | 51.2 |
| MCFairMOT +HardNet | 48.8 | 13.4 | 10.8 | 80.5 | 47.8 |



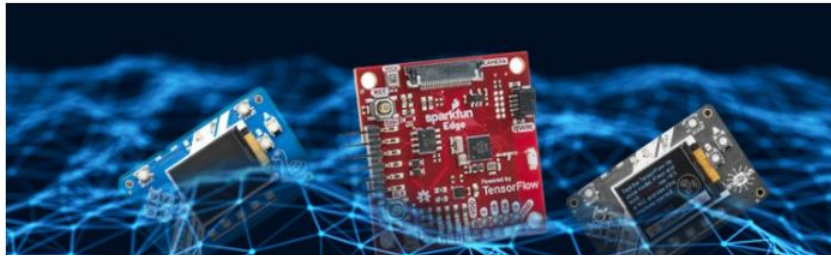
Top Choice for Object Detection on Low-Memory Edge Devices



Rugved Hattekar
Mar 24, 2021 · 5 min read · Listen



Which Deep Learning Framework to choose for Object Detection on low memory Edge Devices?



| | Head Network | Backbone Network | mAP | Inference Time (ms) | FPS |
|---|--------------|------------------|------|---------------------|-----|
| 1 | SSD | ResNet 101 | 31.2 | 125 | 9 |
| 2 | YOLOv3 | ResNet 101 | 31 | 41 | 37 |
| 3 | CenterNet | ResNet-101 | 34.6 | 22 | 45 |

| | Head Network | Backbone Network | mAP | Inference Time (ms) | FPS |
|---|--------------|------------------|------|---------------------|-----|
| 1 | YOLO v3 | DarkNet-53 | 33 | 22 | 20 |
| 2 | CenterNet | DLA | 41.6 | 28 | 35 |

| | Head Network | Backbone Network | mAP | Inference Time (ms) | FPS |
|---|--------------|------------------|------|---------------------|-----|
| 1 | CenterNet | HarDnet-85 | 43.6 | 22 | 45 |

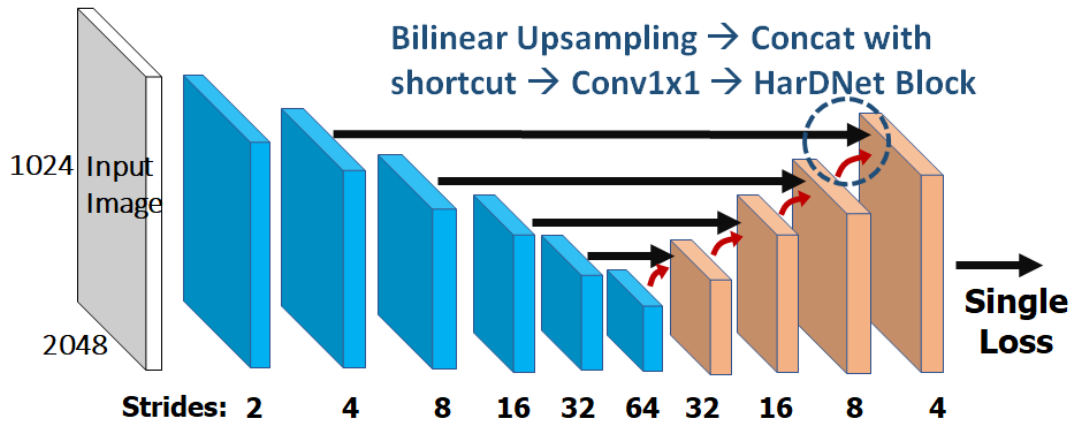
...HarDNet as a backbone, the **CenterNet performs even better** by reducing the inference time and increasing the FPS even more. This type of performance is **well suited for an edge-device implementation** where we can acquire high FPS with low inference speed.

Finally, HarDNet is used **as a backbone to SSD object detector** to verify the robustness of the HarDnet feature extractor ...HarDNet considerably reduces the inference time (~80%) of SSD ... This shows that **HarDNet should be a top choice for the deployment on low-memory devices.**

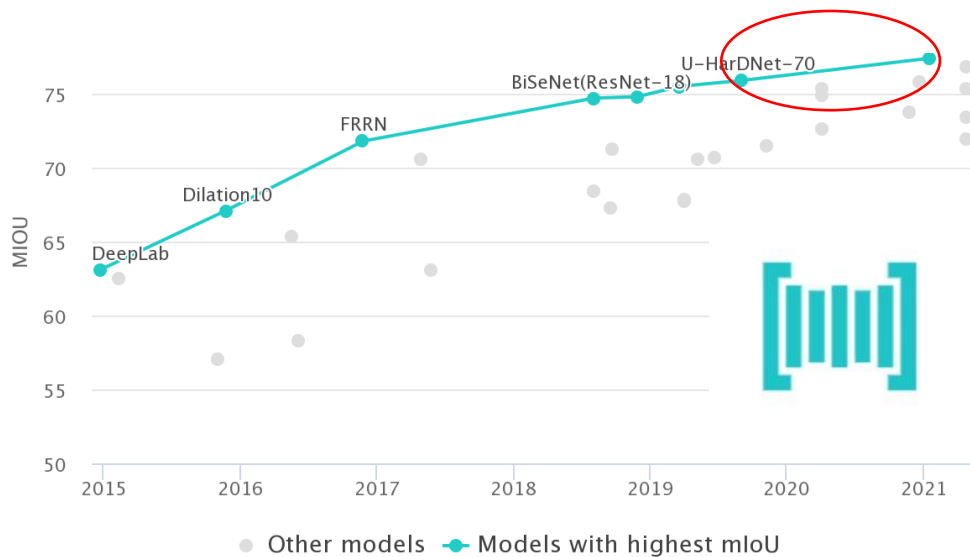
| | Head Network | Backbone Network | mAP | Inference Time (ms) | FPS |
|---|--------------|------------------|------|---------------------|-----|
| 1 | SSD | HarDnet-85 | 35.1 | 25 | 39 |
| 2 | SSD | ResNet-101 | 31.2 | 125 | 9 |

Real-Time Semantic Segmentation of High-Definition Video

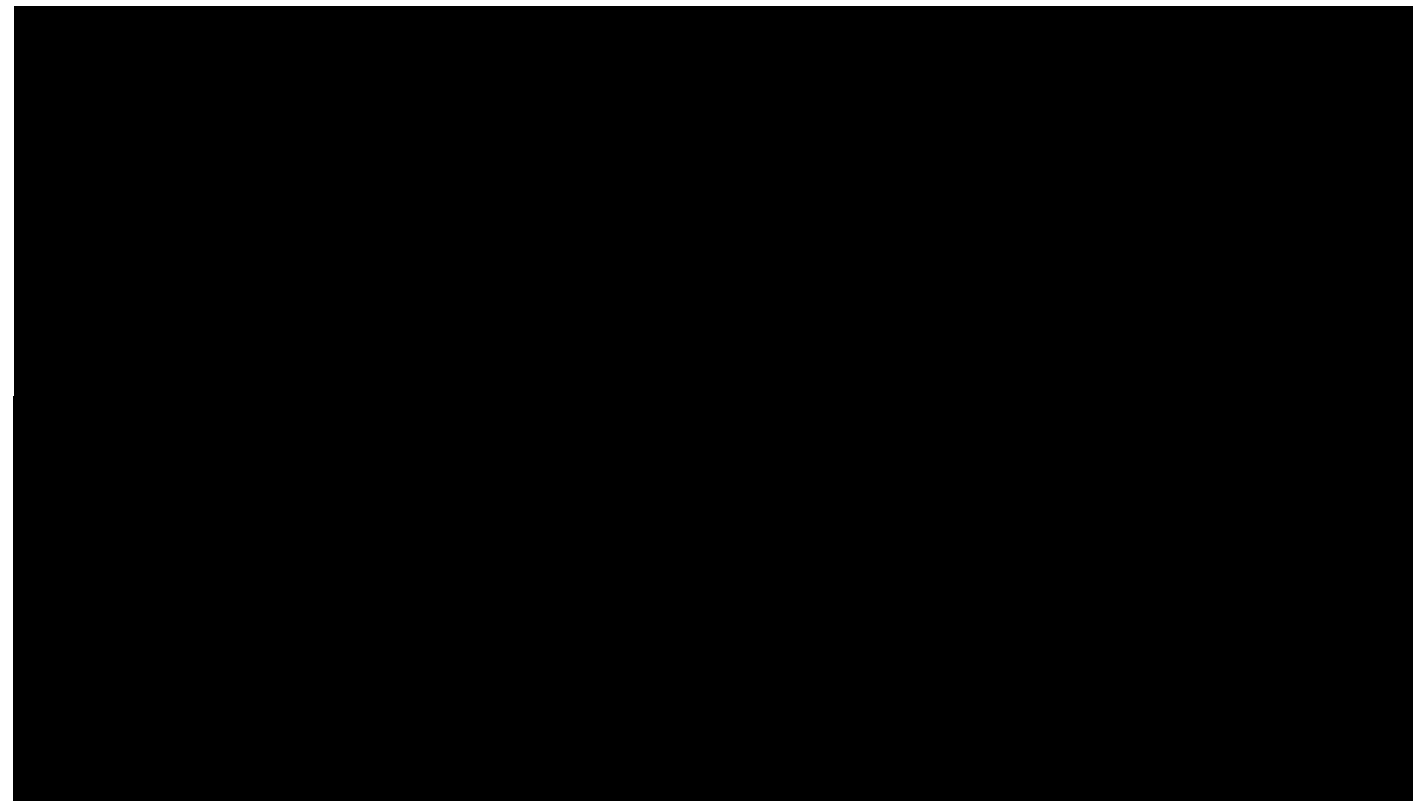
FCHarDNet (Fully Convolutional, U-HarDNet) for Real-Time Semantic Segmentation



FC-HarDNet 70



Cityscape Benchmark



FCHarDNet for Autonomous Driving



Annotating Automotive Radar efficiently: Semantic Radar Labeling Framework (SeRaLF)

Simon T. Isele^{1,3,4*}, Marcel P. Schilling^{1,2*}, Fabian E. Klein¹, J. Marius Zoellner^{3,4}

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²Institute for Automation and Applied Informatics

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Karlsruhe Institute of Technology, Karlsruhe, Germany
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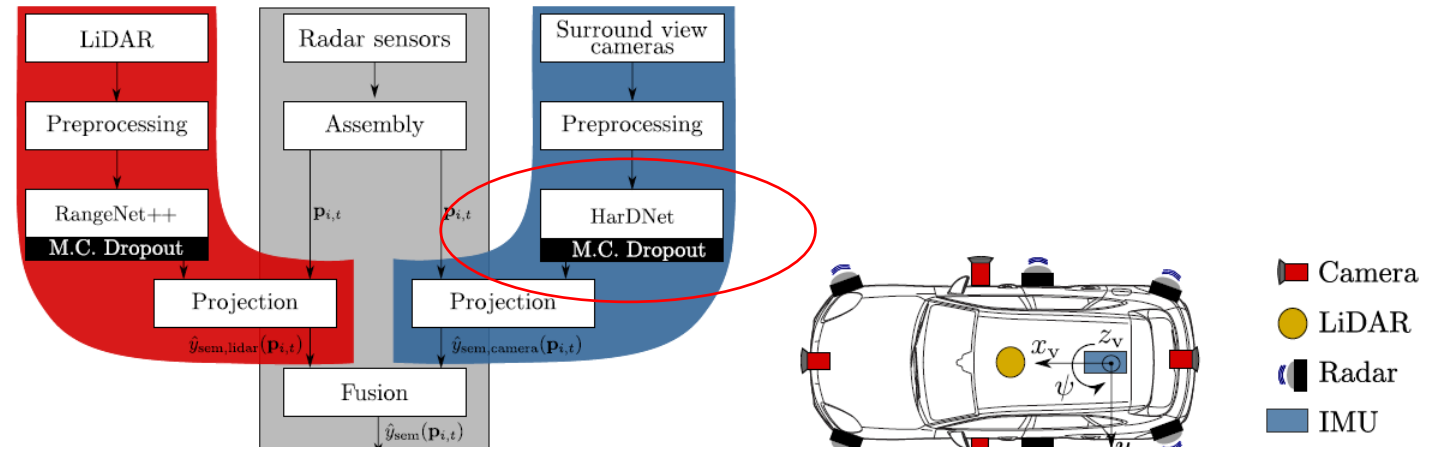


Figure 3: Results of semantic segmentation on fisheye camera (a) and after preprocessing (b).

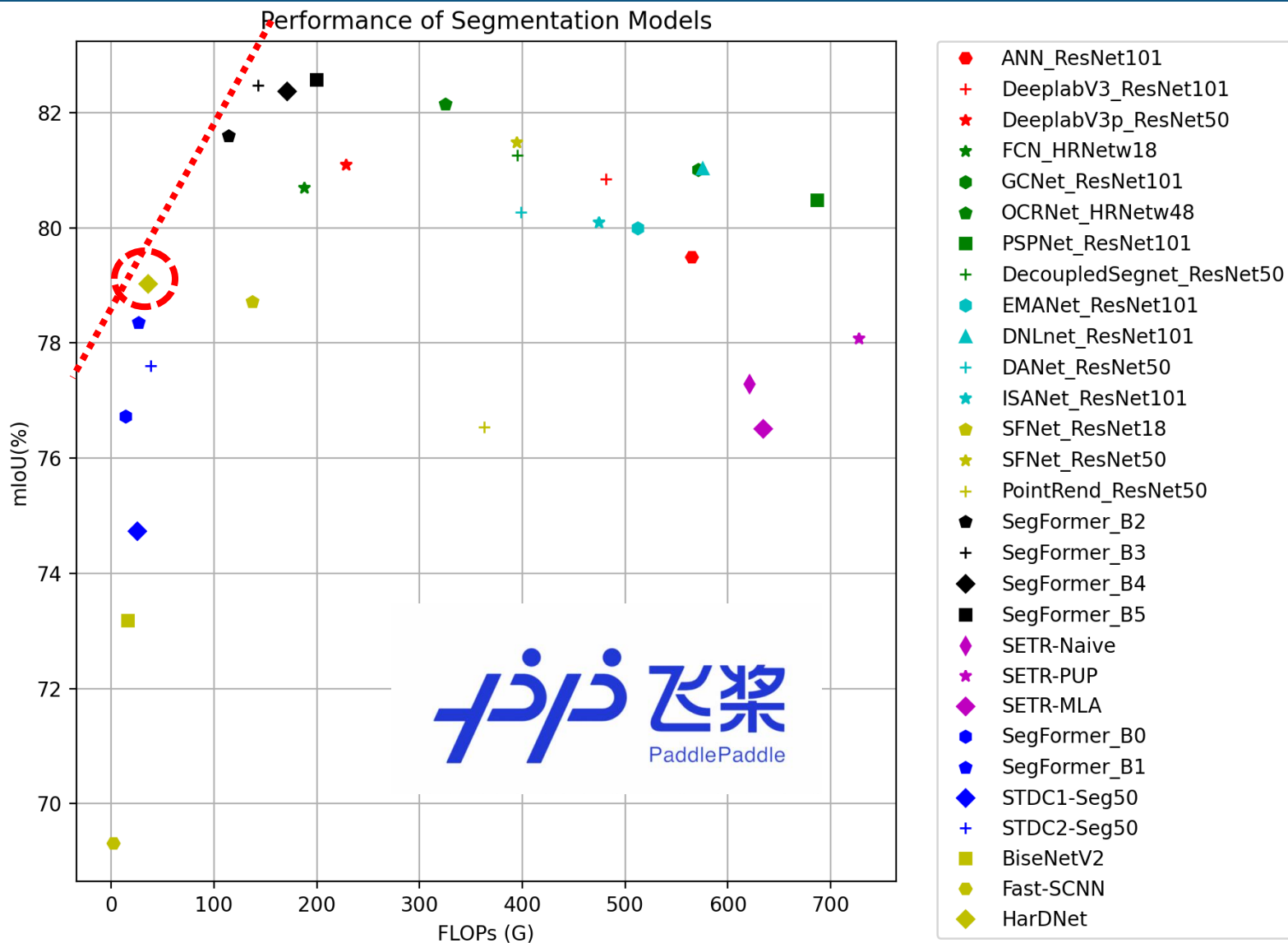


Figure 4: Results of semantic segmentation on LiDAR image (a) and scene overview (b).

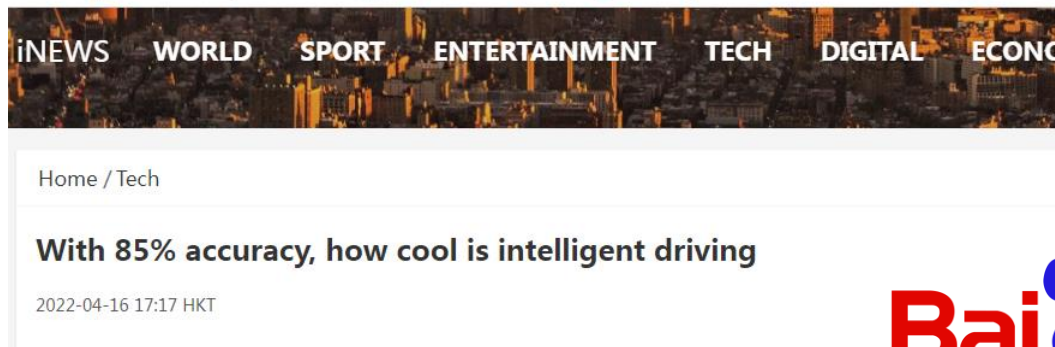




FCharDNet in Baidu PaddleSeg Model Zoo



FCharDNet + PPYOLOv2 for Intelligent Driving



FCHarDNet for Unmanned Railroad Trains

Оптимизация модели нейронной сети U-HarDNet-70 для сегментации железнодорожного пути

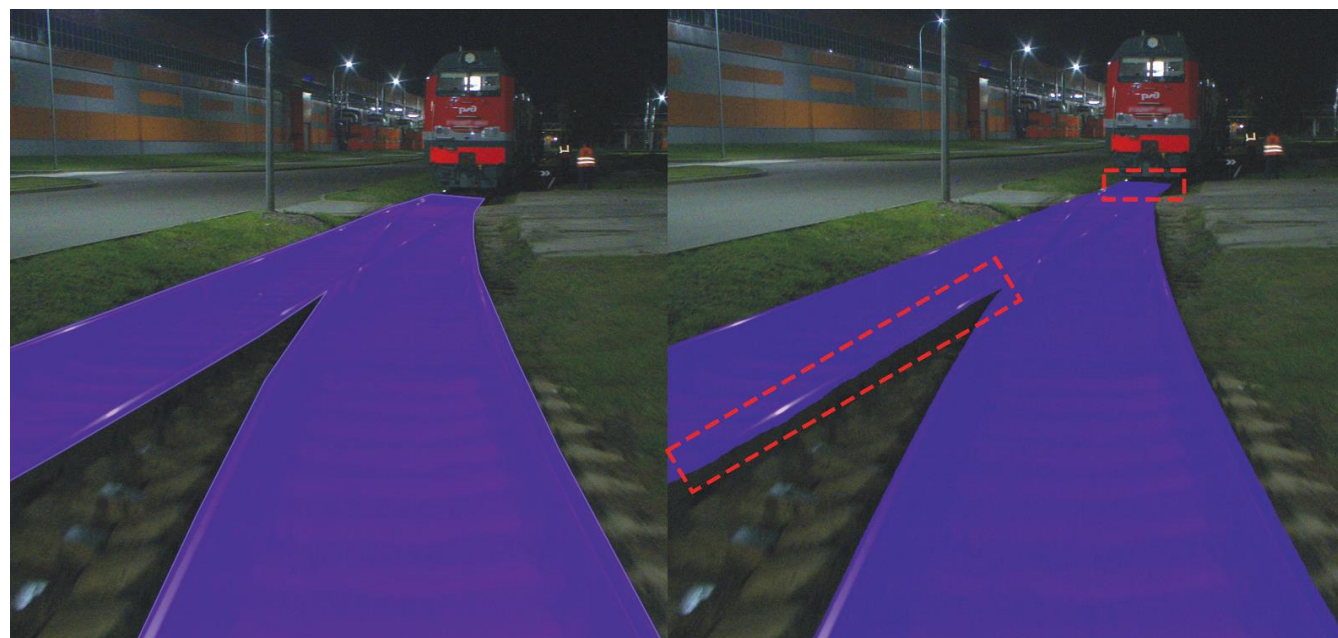
LocoTech SIGNAL



П. Е. Машченко,
канд. техн. наук,
зам. генерального
директора
ООО «ЛокоТех-Сигнал»



П. П. Ширяев,
специалист
по компьютерному
зрению
ООО «ЛокоТех-Сигнал»



CSPHarDNet = CSP-Net + HarDNet for Autonomous Parking



Deep-Learning-Based Parking Area and Collision Risk Area Detection Using AVM in Autonomous Parking Situation

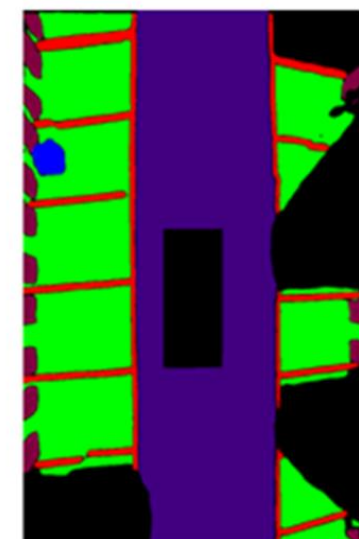
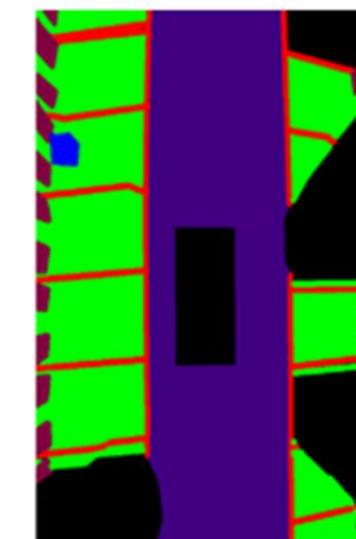
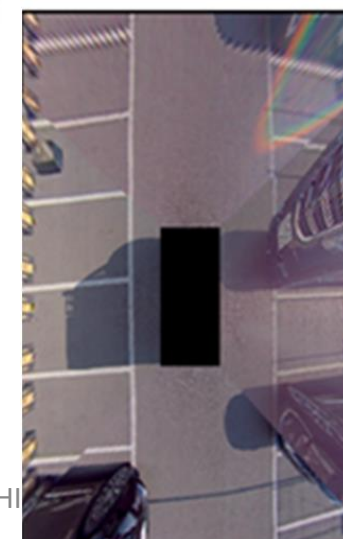
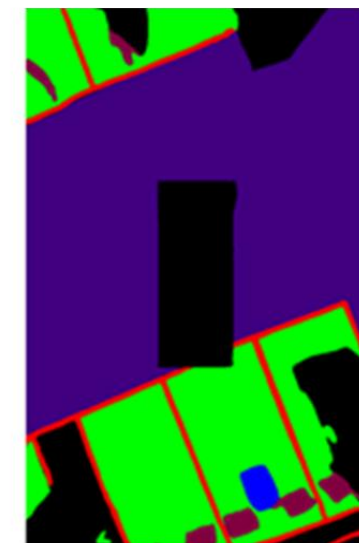
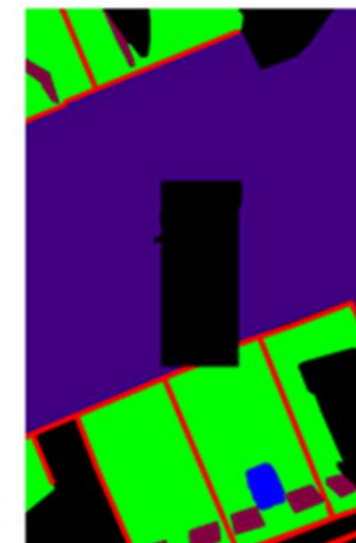
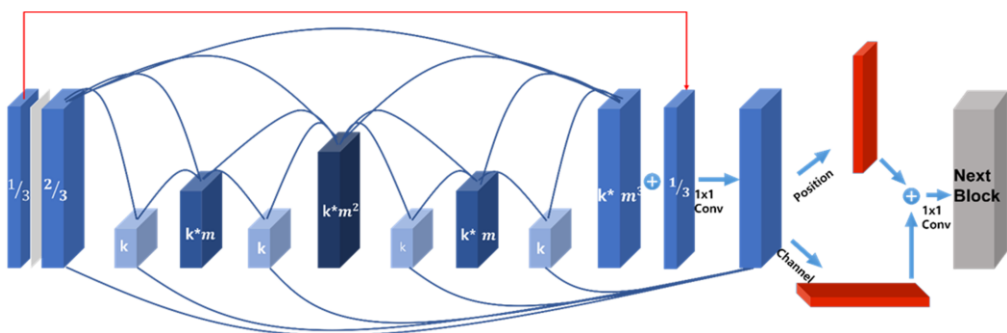
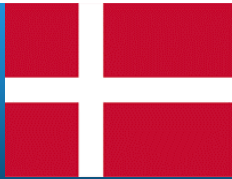


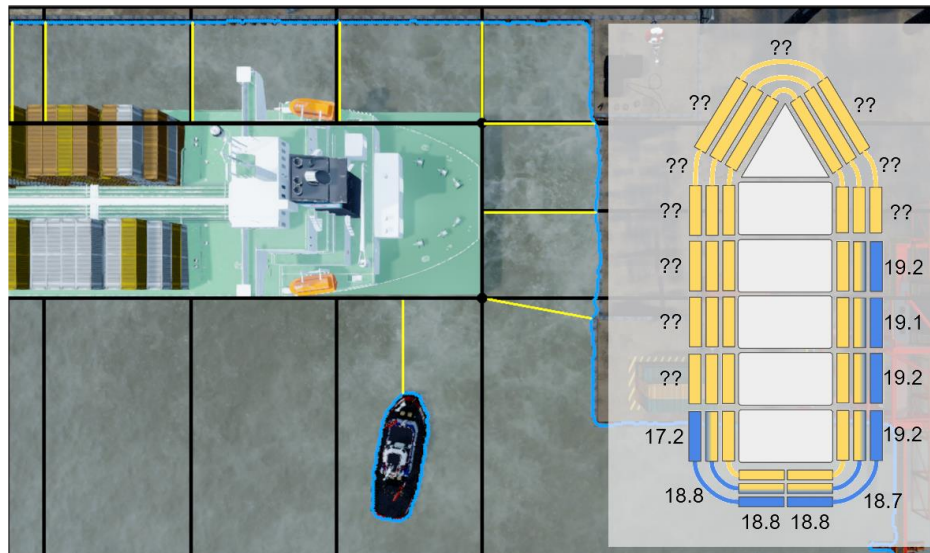
Table 4. NIA dataset results.

| Model | mIoU(%) | BFLOPS | FPS(PC) | FPS(Xavier) |
|----------------------|---------|--------|---------|-------------|
| HarDNet | 83.31 | 110.39 | 15.44 | 15.92 |
| CSPDenseNet | 79.84 | 60.356 | 19.98 | 20.11 |
| CSPHarDNet | 81.89 | 72.847 | 18.15 | 18.36 |
| Attention CSPHarDNet | 83.76 | 81.443 | 17.33 | 17.45 |

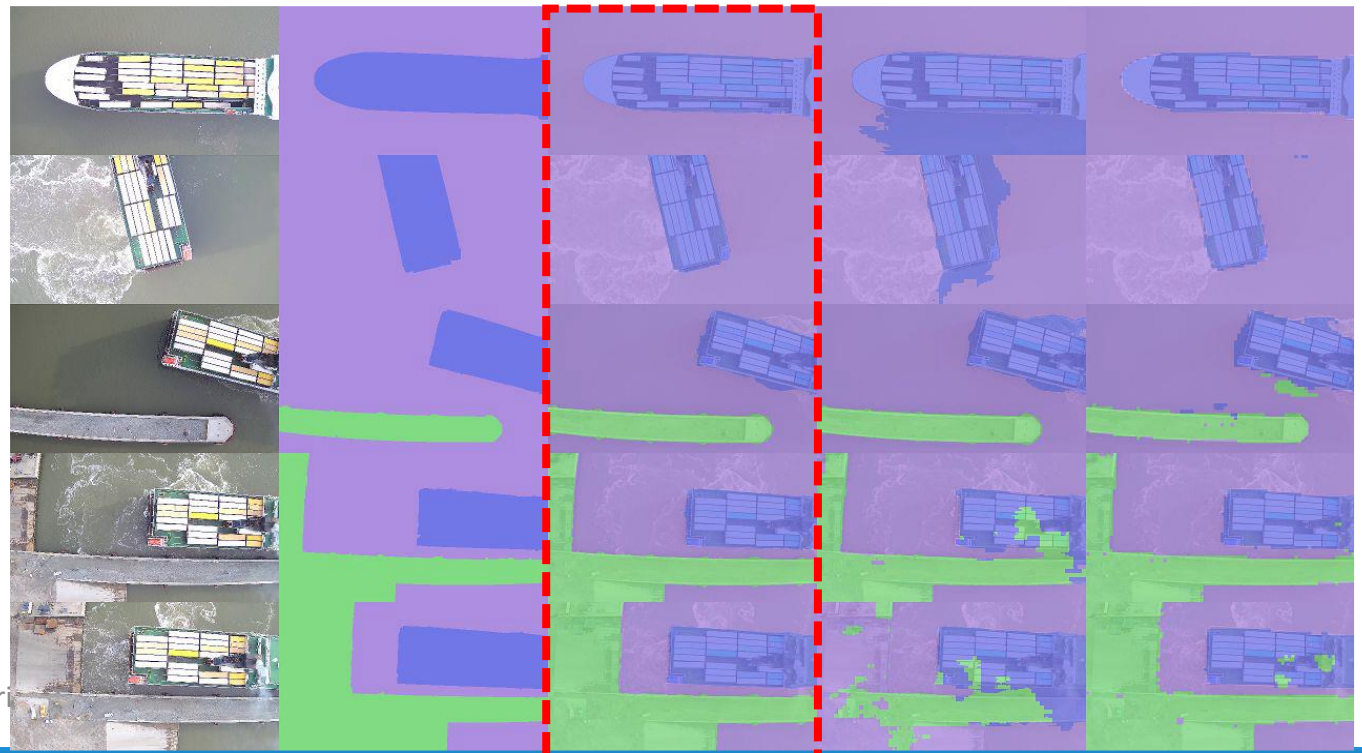
FCHarDNet for Safe Vessel Navigation



Safe Vessel Navigation Visually Aided by Autonomous Unmanned Aerial Vehicles in Congested Harbors and Waterways



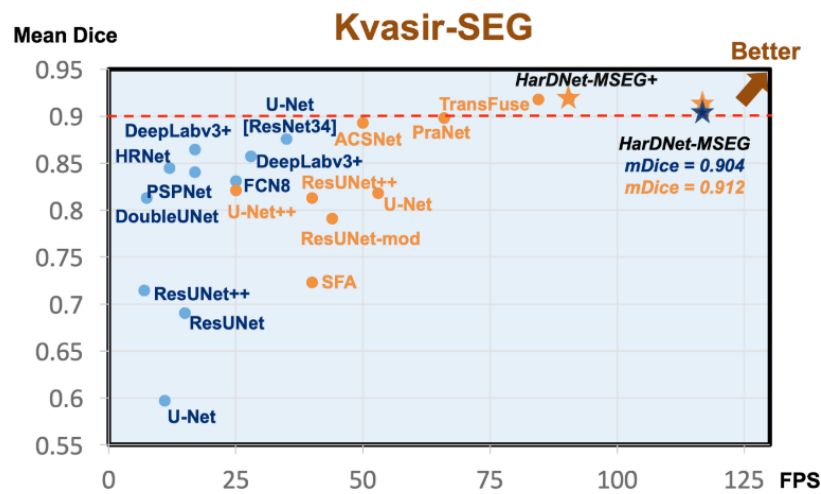
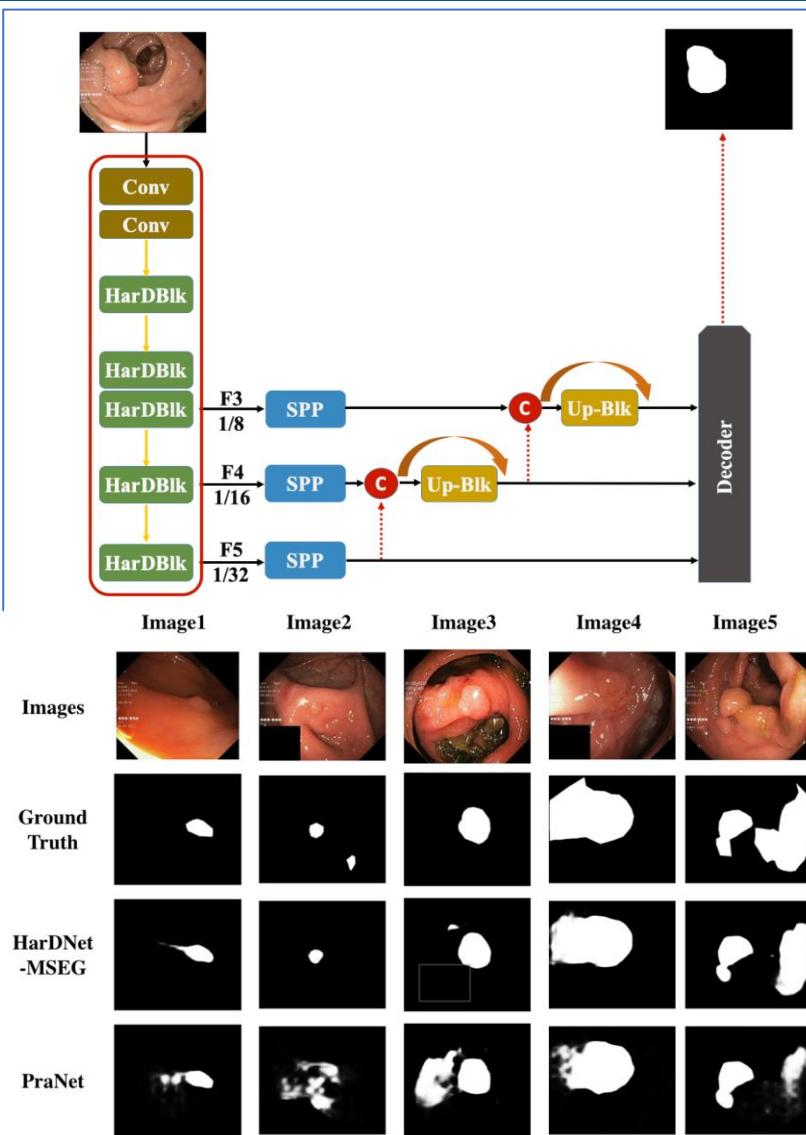
| Model | Dataset | Mean accuracy | IoU | | | | Speed (FPS) | Resolution (w,h) | Params |
|------------|---------|---------------|---------|-------|------|------|-------------|------------------|--------|
| | | | Unknown | Water | Ship | Mean | | | |
| BiSeNet v2 | Val | 96.4 | 91. | 97.7 | 93.3 | 94.0 | 133.43 | 512x288 | 3.5M |
| | Test | 75.4 | 47.5 | 70.2 | 54.5 | 57.4 | | | |
| HarDNet | Val | 98.6 | 96.3 | 98.7 | 96.6 | 97.2 | 91.75 | 640x360 | 4M |
| | Test | 97.3 | 90.9 | 96.6 | 92.6 | 93.4 | | | |
| DDRNet-23 | Val | 97.4 | 92.5 | 97.6 | 92.9 | 94.3 | 100.12 | 640x360 | 7.6M |
| | Test | 86.4 | 73.4 | 80.4 | 62. | 72. | | | |



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Medical Imaging – Polyps Segmentation

HarDNet-MSEG for Endoscopy Polyp Segmentation

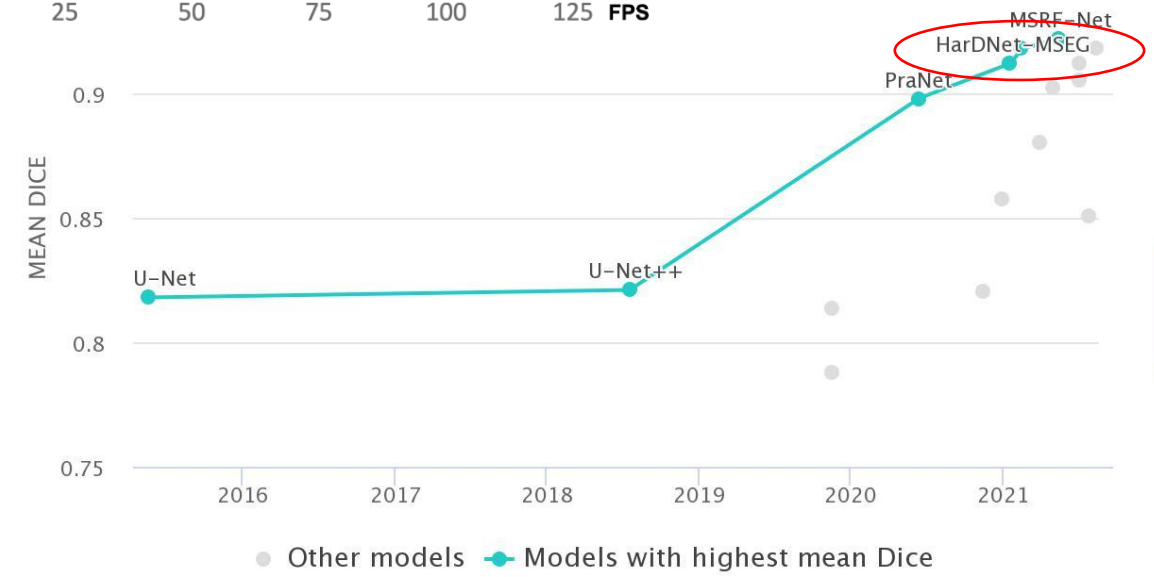


arXiv

HarDNet-MSEG Public

Forked from DengPingFan/PraNet

Python 112 30



HarDNet-MSEG in XILINX VITIS AI Library

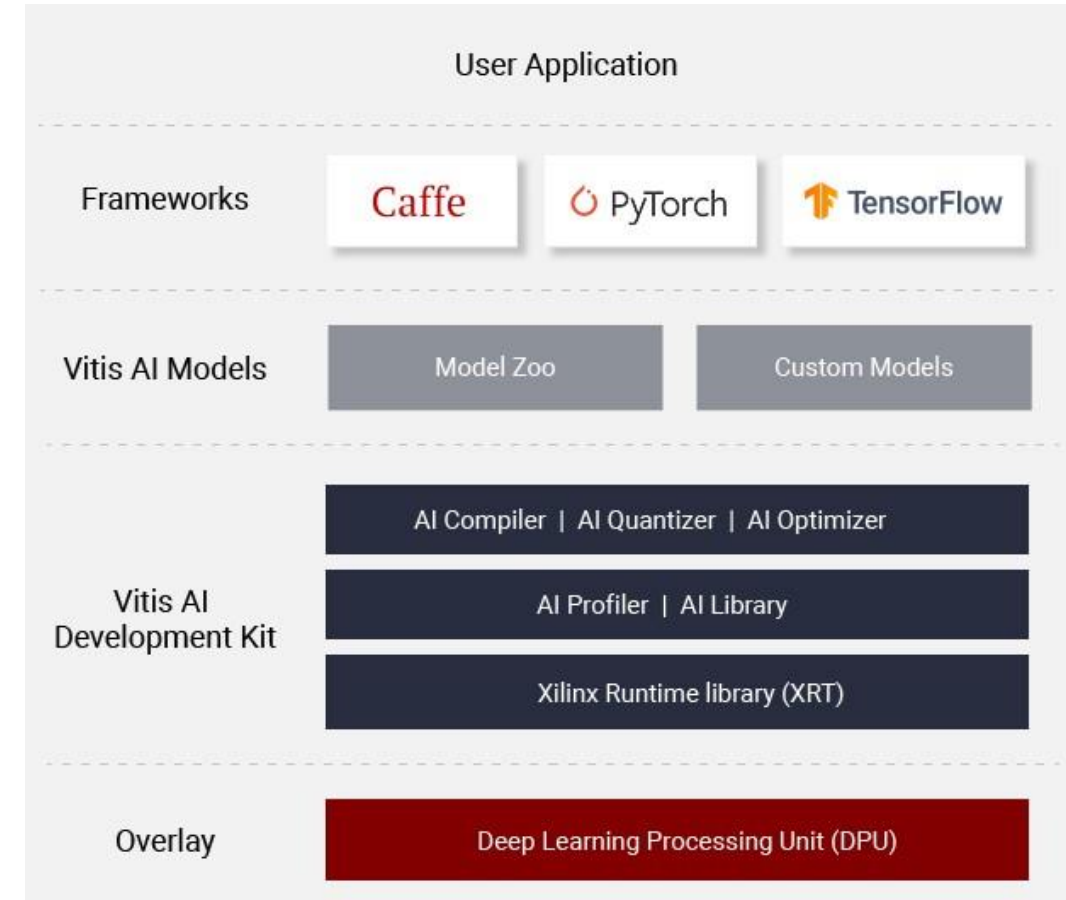
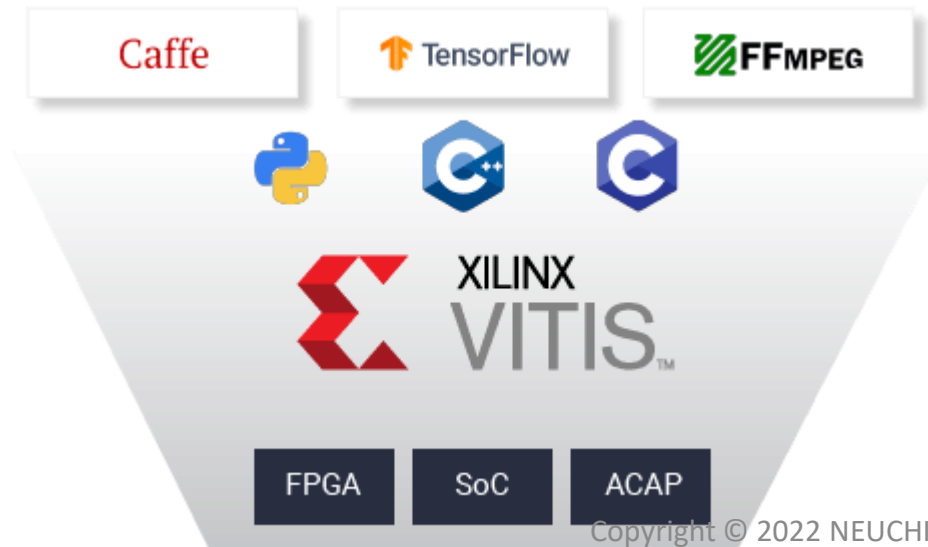


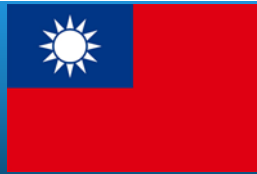
The following table lists the Polyp Segmentation models supported by the Vitis AI library.

Table: Polyp Segmentation Models

| No | Model Name | Framework |
|----|-----------------|-----------|
| 1 | HardNet_MSeg_pt | PyTorch |

<https://docs.xilinx.com/r/en-US/ug1354-xilinx-ai-sdk/Polyp-Segmentation>





HarDNet-MSEG X8 – US\$10,000 Prize

<https://www.hackster.io/contests/xilinxadaptivecomputing2021>



Data Center AI

1st place was awarded a \$10,000 Visa Gift Card (\$10,000 value), 2nd place was awarded a \$5,000 Visa Gift Card (\$5,000 value), and 3rd place was awarded a \$3,000 Visa Gift Card (\$3,000 value)

2021 Xilinx Adaptive Computing Challenge (XACC)

- 1649 participants
- 168 submissions
- Data Center AI using Xilinx VCK5000 Card
- Judges are CTO & VPs



NYCity

DATA CENTER AI: 1ST PLACE
Instant Medical Image Analysis Aid for 8 Clinic Exam Rooms

Stefan Blattmann

DATA CENTER AI: 2ND PLACE
Green computing: Versal based image restoration pipeline

TheMatrix

DATA CENTER AI: 3RD PLACE
Deepfakes C-L-I on VCK5000

**1st Place Award Winner: Prof. Juinn-Dar Huang's Lab
National Yang Ming Chiao Tung University, Taiwan**

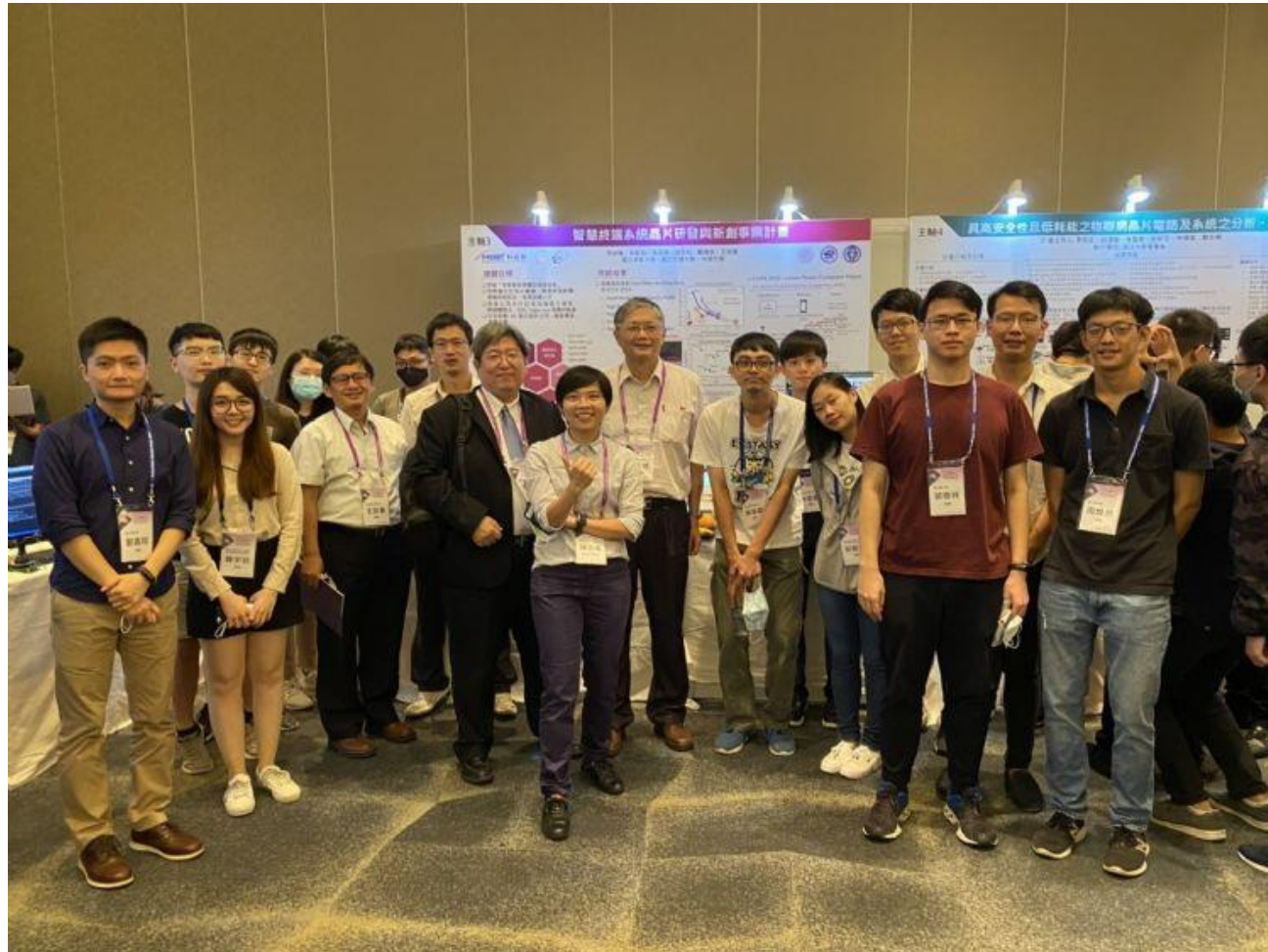
國內醫生怎麼說？

After validating with 100+ captured videos (15 min+)

... the gastroenterologist has reviewed the results and found them to be very good. The model generally skipped proliferative polyps (less pathogenic) and **detect all adenomatous polyps (prone to become cancer)**. This is helpful for clinicians....



感謝射月計畫團隊



國立陽明交通大學

NATIONAL YANG MING CHIAO TUNG UNIVERSITY

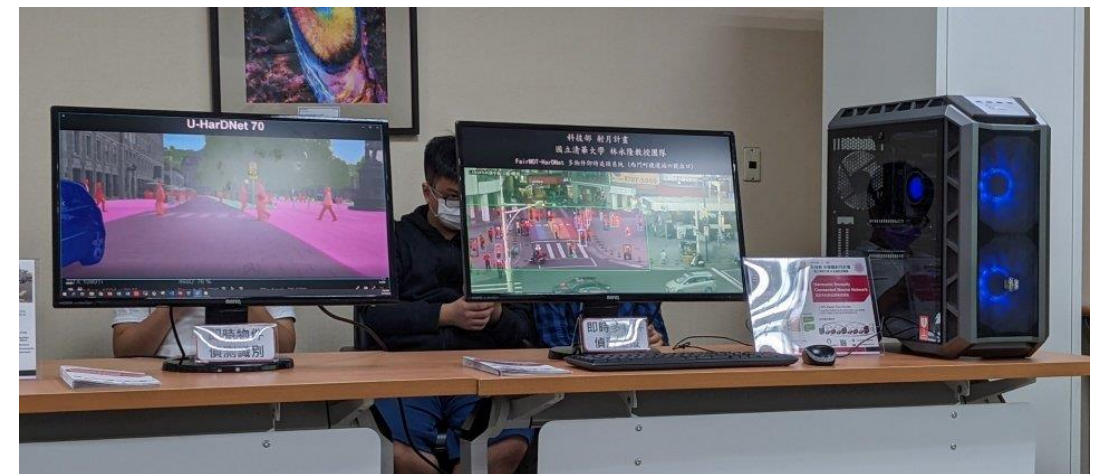


國立清華大學



中原大學

Chung Yuan Christian University



感謝國網中心



十、推動科研卓越發展，落實跨域規劃合作

(一)深耕基礎科研，落實在地性及國際性，提升科研價值貢獻：

- 1、研發最適合硬體實現之類神經網路架構 HarDNet，在影像辨識、物件識別、物件追蹤、視訊語意分割等應用都有優異表現，對於惡意攻擊具更強免疫力。相關技術已成立新創公司，所開發之神經網路加速器矽智財，獲得知名大廠採用，已完成 MPW 驗證，即將進入量產。
- 2、開發全球最靈敏之重金屬感測晶片，可輕易且迅速地偵測低於政府飲用水法規閾值以下 1 萬倍之重金屬濃度；另將光譜儀微縮成一顆晶片(光譜晶片)，用於建置新冠病毒抗體定量篩檢機臺，可於 15 分鐘至 20 分鐘內篩檢出陽性病患，與國內醫療系統密切合作，並獲得國際高度重視。
- 3、發現罕見疾病早衰症致病關鍵因素「細胞表面之初級纖毛異常」，有助瞭解早衰症及其他核纖層蛋白病症之致病機制，以供開發早衰症治療策略。
- 4、透過精準運動科學跨領域整合研究，已成功開發棒球之電子好球帶及 3D 動

Thank You!!

Contact

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