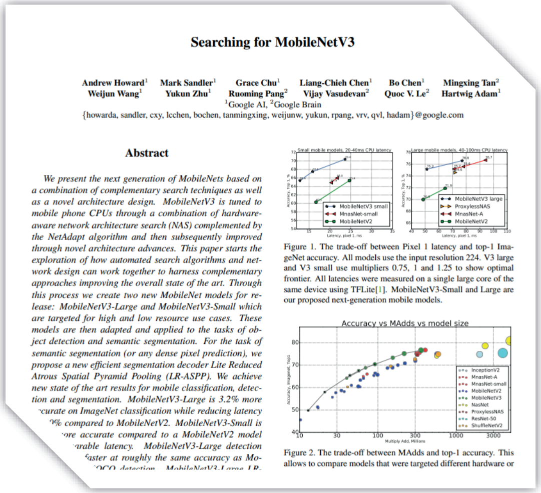
Paper



Searching for MobileNetV3

Andrew Howard[1] Mark Sandler[1] Grace Chu[1] Liang-Chieh Chen[1] Bo Chen[1] Mingxing Tan[2]
Weijun Wang[1] Yukun Zhu[1] Ruoming Pang[2] Vijay Vasudevan[2] Quoc V. Le[2] Hartwig Adam[1]
[1]Google AI, [2]Google Brain
{howarda, sandler, cxy, lcchen, bochen, tanmingxing, weijunw, yukun, rpang, vrv, qvl, hadam}@google.com

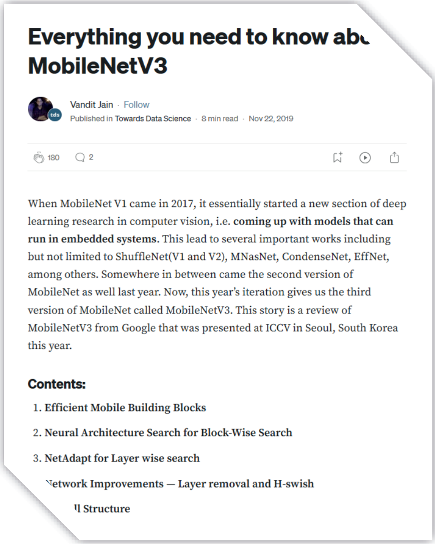
Abstract

We present the next generation of MobileNets based on a combination of complementary search techniques as well as a novel architecture design. MobileNetV3 is tuned to mobile phone CPUs through a combination of hardware-aware network architecture search (NAS) complemented by the NetAdapt algorithm and then subsequently improved through novel architecture advances. This paper starts the exploration of how automated search algorithms and network design can work together to harness complementary approaches improving the overall state of the art. Through this process we create two new MobileNet models for release: MobileNetV3-Large and MobileNetV3-Small which are targeted for high and low resource use cases. These models are then adapted and applied to the tasks of object detection and semantic segmentation. For the task of semantic segmentation (or any dense pixel prediction), we propose a new efficient segmentation decoder Lite Reduced Atrous Spatial Pyramid Pooling (LR-ASPP). We achieve new state of the art results for mobile classification, detection and segmentation. MobileNetV3-Large is 3.2% more curate on ImageNet classification while reducing latency 0% compared to MobileNetV2. MobileNetV3-Small is ore accurate compared to a MobileNetV2 model arable latency. MobileNetV3-Large detection faster at roughly the same accuracy as Mo- OCO detection. MobileNetV3-Large LR-

Figure 1. The trade-off between Pixel 1 latency and top-1 ImageNet accuracy. All models use the input resolution 224. V3 large and V3 small use multipliers 0.75, 1 and 1.25 to show optimal frontier. All latencies were measured on a single large core of the same device using TFLite[1]. MobileNetV3-Small and Large are our proposed next-generation mobile models.

Figure 2. The trade-off between MAdds and top-1 accuracy. This allows to compare models that were targeted different hardware or

Gray Literature



Everything you need to know abo MobileNetV3

Vandit Jain · Follow
Published in Towards Data Science · 8 min read · Nov 22, 2019

When MobileNet V1 came in 2017, it essentially started a new section of deep learning research in computer vision, i.e. **coming up with models that can run in embedded systems.** This lead to several important works including but not limited to ShuffleNet(V1 and V2), MNasNet, CondenseNet, EffNet, among others. Somewhere in between came the second version of MobileNet as well last year. Now, this year's iteration gives us the third version of MobileNet called MobileNetV3. This story is a review of MobileNetV3 from Google that was presented at ICCV in Seoul, South Korea this year.

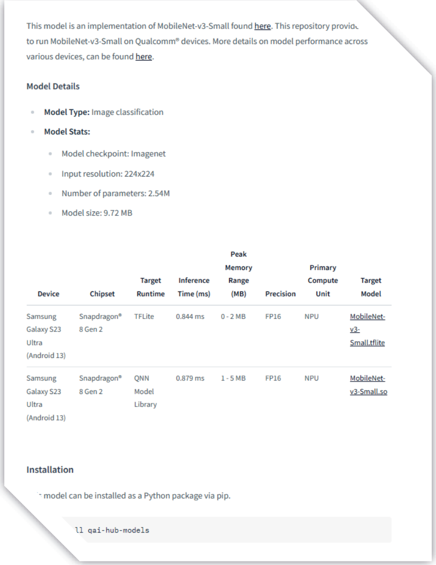
Contents:

1. **Efficient Mobile Building Blocks**
2. **Neural Architecture Search for Block-Wise Search**
3. **NetAdapt for Layer wise search**

etwork Improvements — Layer removal and H-swish

l Structure

Model Card



This model is an implementation of MobileNet-v3-Small found here. This repository provid to run MobileNet-v3-Small on Qualcomm® devices. More details on model performance across various devices, can be found here.

Model Details

- **Model Type:** Image classification
- **Model Stats:**
  - Model checkpoint: Imagenet
  - Input resolution: 224x224
  - Number of parameters: 2.54M
  - Model size: 9.72 MB

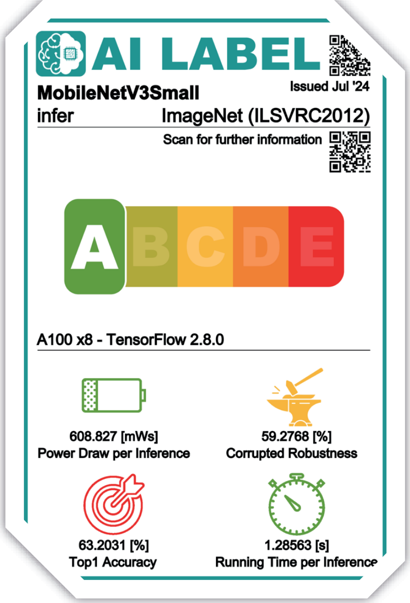
Device	Chipset	Target Runtime	Inference Time (ms)	Peak Memory Range (MB)	Precision	Primary Compute Unit	Target Model
Samsung Galaxy S23 Ultra (Android 13)	Snapdragon® 8 Gen 2	TFLite	0.844 ms	0 - 2 MB	FP16	NPU	MobileNet-v3-Small.tflite
Samsung Galaxy S23 Ultra (Android 13)	Snapdragon® 8 Gen 2	QNN Model Library	0.879 ms	1 - 5 MB	FP16	NPU	MobileNet-v3-Small.so

Installation

model can be installed as a Python package via pip.

```
ll qai-hub-models
```

AI Label



MobileNetV3Small Issued Jul '24
infer ImageNet (ILSVRC2012)
Scan for further information

A100 x8 - TensorFlow 2.8.0

608.827 [mWs]
Power Draw per Inference

59.2768 [%]
Corrupted Robustness

63.2031 [%]
Top1 Accuracy

1.28563 [s]
Running Time per Inference

Benchmark (PWC)

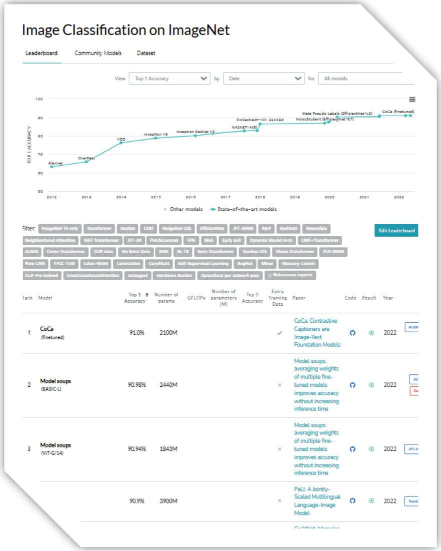
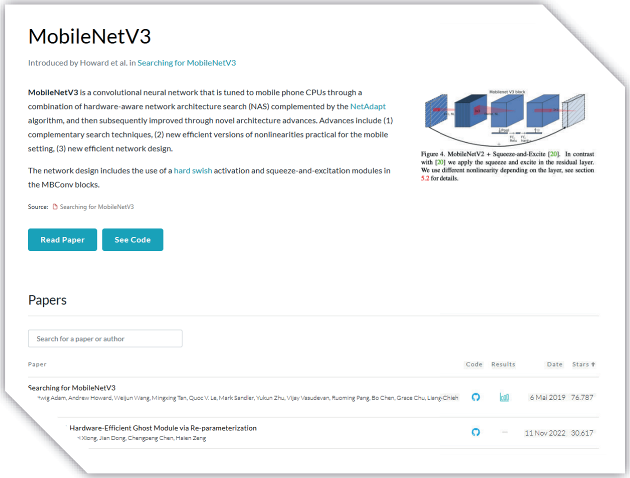


Image Classification on ImageNet

Rank	Model	Top 1 Accuracy ↑	Number of params	GFLOPs	Number of parameters (M)	Top 5 Accuracy	Extra Training Data	Paper	Code	Result	Year
1	CoCa (finetuned)	91.0%	2100M				✓	CoCa: Contrastive Captioners are Image-Text Foundation Models			2022
2	Model soups (BASIC-L)	90.98%	2440M				×	Model soups: averaging weights of multiple fine-tuned models improves accuracy without increasing inference time			2022
3	Model soups (ViT-G/14)	90.94%	1843M				×	Model soups: averaging weights of multiple fine-tuned models improves accuracy without increasing inference time			2022
		90.9%	3900M				×	PaLI: A Jointly-Scaled Multilingual Language-Image Model			2022

Platform (PWC)



MobileNetV3

Introduced by Howard et al. in Searching for MobileNetV3

MobileNetV3 is a convolutional neural network that is tuned to mobile phone CPUs through a combination of hardware-aware network architecture search (NAS) complemented by the NetAdapt algorithm, and then subsequently improved through novel architecture advances. Advances include (1) complementary search techniques, (2) new efficient versions of nonlinearities practical for the mobile setting, (3) new efficient network design.

The network design includes the use of a hard swish activation and squeeze-and-excitation modules in the MBConv blocks.

Figure 4. MobileNetV2 + Squeeze-and-Excite [20]. In contrast with [20] we apply the squeeze and excite in the residual layer. We use different nonlinearity depending on the layer, see section 5.2 for details.

Source: Searching for MobileNetV3

Papers

Paper	Code	Results	Date	Stars ↑
Searching for MobileNetV3 twig Adam, Andrew Howard, Weijun Wang, Mingxing Tan, Quoc V. Le, Mark Sandler, Yukun Zhu, Vijay Vasudevan, Ruoming Pang, Bo Chen, Grace Chu, Liang-Chieh			6 Mai 2019	76.787
Hardware-Efficient Ghost Module via Re-parameterization i Xiong, Jian Dong, Chengpeng Chen, Haien Zeng		—	11 Nov 2022	30.617