Transformers and large-kernel CNNs

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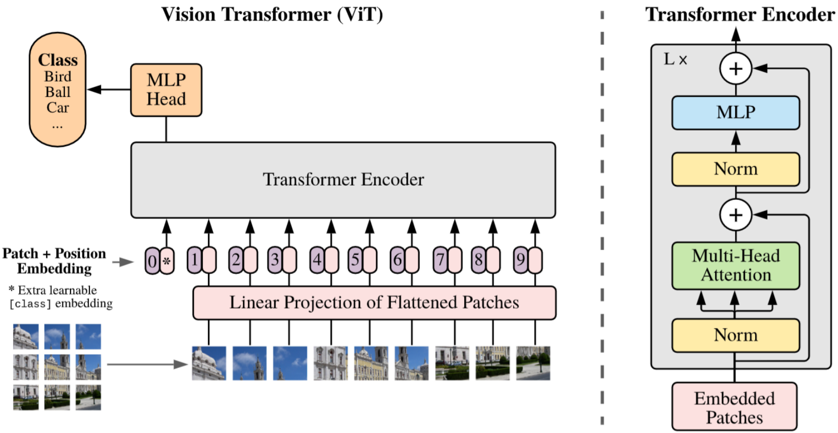
16 October 2024

Outline

Vision Transformer



Dosovitskiy et al. An Image is Worth 16×16 Words: Transformers for Image Recognition at Scale. ICLR 2021

Multi-Head Self-Attention

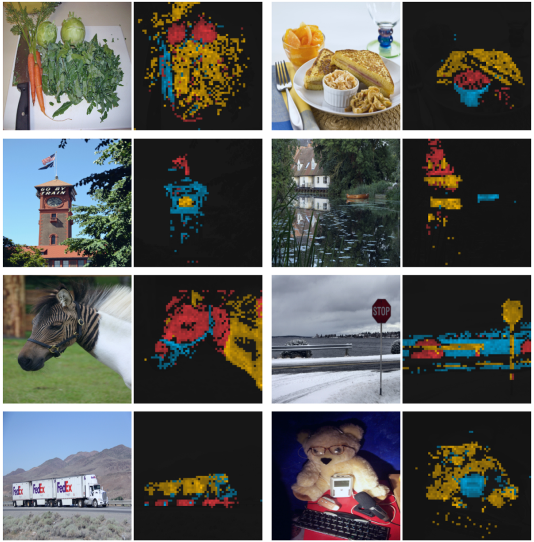
$$[q, k, v] = zU_{qkv}, \qquad z \in \mathbb{R}^{N\times D}, \quad U_{qkv} \in \mathbb{R}^{D\times 3D_h}$$

$$A = \mathrm{softmax}(qk^T/\sqrt{D_h}), \qquad A \in \mathbb{R}^{N\times N}$$

$$\mathrm{SA}(z) = Av$$

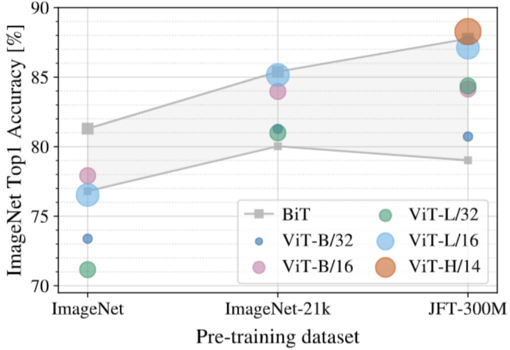
$$\mathrm{MSA}(z) = [\mathrm{SA}_1(z); \mathrm{SA}_2(z); \dots; \mathrm{SA}_k(z)]U_{msa}, \qquad U_{msa} \in \mathbb{R}^{k\cdot D_h\times D}$$

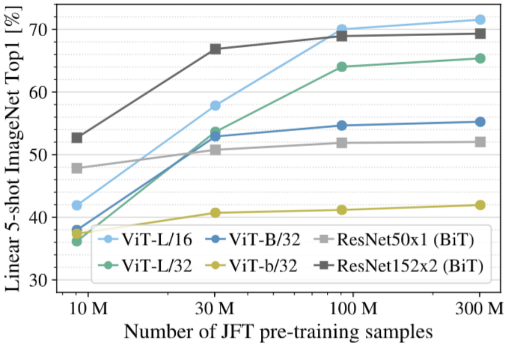
MSA visualization, 8×8 patches



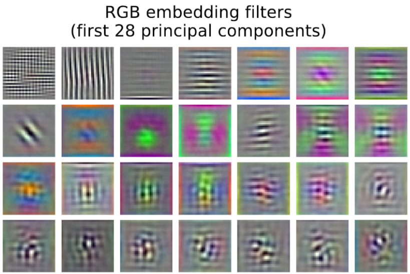
Vision Transformer

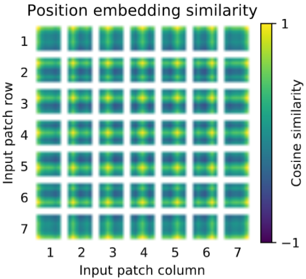
Model	Layers	Hidden size D	MLP size	Heads	Params
ViT-Base	12	768	3072	12	86M
ViT-Large	24	1024	4096	16	307M
ViT-Huge	32	1280	5120	16	632M

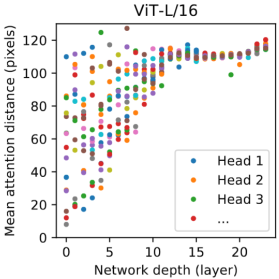




Vision Transformer







Data-Efficient Transformer

Methods	ViT-B	DeiT-B
Epochs	300	300
Batch size	4096	1024
Optimizer	AdamW	AdamW
learning rate	0.003	$0.0005 \times \frac{\text{batchsize}}{512}$
Learning rate decay	cosine	cosine
Weight decay	0.3	0.05
Warmup epochs	3.4	5
Label smoothing ε	✗	0.1
Dropout	0.1	✗
Stoch. Depth	✗	0.1
Repeated Aug	✗	✓
Gradient Clip.	✓	✗
Rand Augment	✗	9/0.5
Mixup prob.	✗	0.8
Cutmix prob.	✗	1.0
Erasing prob.	✗	0.25

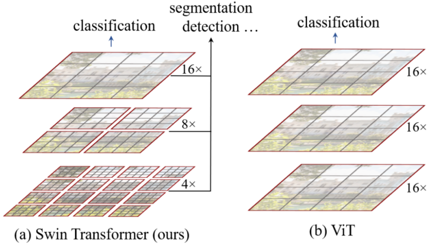
Network	nb of param.	image size	im/s	ImNet top-1	Real top-1	V2 top-1
ResNet-18	12M	224	4458.4	69.8	77.3	57.1
ResNet-50	25M	224	1226.1	76.2	82.5	63.3
ResNet-101	45M	224	753.6	77.4	83.7	65.7
ResNet-152	60M	224	526.4	78.3	84.1	67.0
RegNetY-4GF⋆	21M	224	1156.7	80.0	86.4	69.4
RegNetY-8GF⋆	39M	224	591.6	81.7	87.4	70.8
RegNetY-16GF⋆	84M	224	334.7	82.9	88.1	72.4
EfficientNet-B0	5M	224	2694.3	77.1	83.5	64.3
EfficientNet-B1	8M	240	1662.5	79.1	84.9	66.9
EfficientNet-B2	9M	260	1255.7	80.1	85.9	68.8
EfficientNet-B3	12M	300	732.1	81.6	86.8	70.6
EfficientNet-B4	19M	380	349.4	82.9	88.0	72.3
EfficientNet-B5	30M	456	169.1	83.6	88.3	73.6
EfficientNet-B6	43M	528	96.9	84.0	88.8	73.9
EfficientNet-B7	66M	600	55.1	84.3	_	_
EfficientNet-B5 RA	30M	456	96.9	83.7	_	_
EfficientNet-B7 RA	66M	600	55.1	84.7	_	_
KDforAA-B8	87M	800	25.2	85.8	_	_
Transformers: training 300 epochs						
ViT-B/16	86M	384	85.9	77.9	83.6	_
ViT-L/16	307M	384	27.3	76.5	82.2	_
DeiT-Ti	5M	224	2536.5	72.2	80.1	60.4
DeiT-S	22M	224	940.4	79.8	85.7	68.5
DeiT-B	86M	224	292.3	81.8	86.7	71.5
DeiT-B↑384	86M	384	85.9	83.1	87.7	72.4
DeiT-Ti⚗	6M	224	2529.5	74.5	82.1	62.9
DeiT-S⚗	22M	224	936.2	81.2	86.8	70.0
DeiT-B⚗	87M	224	290.9	83.4	88.3	73.2
DeiT-B⚗ ↑384	87M	384	85.8	84.5	89.0	74.8
Transformers: training 1000 epochs						
DeiT-Ti⚗	6M	224	2529.5	76.6	83.9	65.4
DeiT-S⚗	22M	224	936.2	82.6	87.8	71.7
DeiT-B⚗	87M	224	290.9	84.2	88.7	73.9
DeiT-B⚗ ↑384	87M	384	85.8	85.2	89.3	75.2

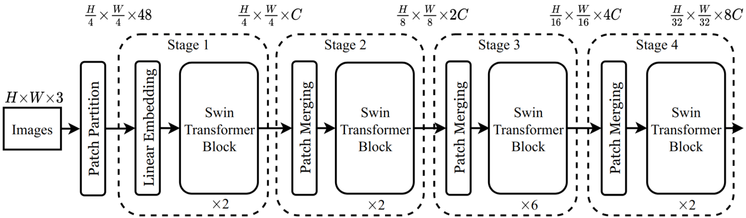
⋆: our trained teachers with SGD, whose optimization procedure is closer to DeiT

Outline

1. Vision Transformer
2. Swin Transformer
3. ConvNeXt
4. MobileNetV4

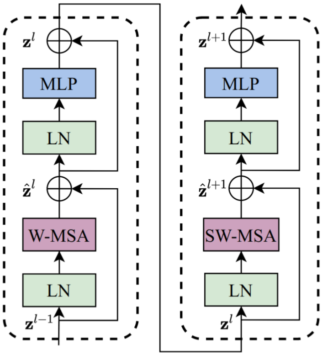
Swin Transformer

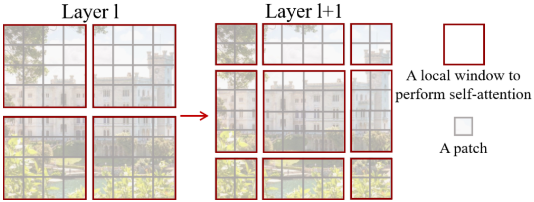




Liu et al. Swin Transformer: Hierarchical Vision Transformer using Shifted Windows. ICCV 2021

Shifted window attention





Include positional information in self-attention:

$$SA(q,k,v) = \mathrm{softmax}(qk^t/\sqrt{D_h} + b)v$$

$$b \in \mathbb{R}^{N \times N}$$

Liu et al. Swin Transformer: Hierarchical Vision Transformer using Shifted Windows. ICCV 2021

Swin variants

	downsp. rate (output size)	Swin-T	Swin-S	Swin-B	Swin-L
stage 1	4× (56×56)	concat 4×4, 96-d, LN	concat 4×4, 96-d, LN	concat 4×4, 128-d, LN	concat 4×4, 192-d, LN
		$\begin{bmatrix}\text{win. sz. } 7\times7,\\ \text{dim 96, head 3}\end{bmatrix} \times 2$	$\begin{bmatrix}\text{win. sz. } 7\times7,\\ \text{dim 96, head 3}\end{bmatrix} \times 2$	$\begin{bmatrix}\text{win. sz. } 7\times7,\\ \text{dim 128, head 4}\end{bmatrix} \times 2$	$\begin{bmatrix}\text{win. sz. } 7\times7,\\ \text{dim 192, head 6}\end{bmatrix} \times 2$
stage 2	8× (28×28)	concat 2×2, 192-d , LN	concat 2×2, 192-d , LN	concat 2×2, 256-d , LN	concat 2×2, 384-d , LN
		$\begin{bmatrix}\text{win. sz. } 7\times7,\\ \text{dim 192, head 6}\end{bmatrix} \times 2$	$\begin{bmatrix}\text{win. sz. } 7\times7,\\ \text{dim 192, head 6}\end{bmatrix} \times 2$	$\begin{bmatrix}\text{win. sz. } 7\times7,\\ \text{dim 256, head 8}\end{bmatrix} \times 2$	$\begin{bmatrix}\text{win. sz. } 7\times7,\\ \text{dim 384, head 12}\end{bmatrix} \times 2$
stage 3	16× (14×14)	concat 2×2, 384-d , LN	concat 2×2, 384-d , LN	concat 2×2, 512-d , LN	concat 2×2, 768-d , LN
		$\begin{bmatrix}\text{win. sz. } 7\times7,\\ \text{dim 384, head 12}\end{bmatrix} \times 6$	$\begin{bmatrix}\text{win. sz. } 7\times7,\\ \text{dim 384, head 12}\end{bmatrix} \times 18$	$\begin{bmatrix}\text{win. sz. } 7\times7,\\ \text{dim 512, head 16}\end{bmatrix} \times 18$	$\begin{bmatrix}\text{win. sz. } 7\times7,\\ \text{dim 768, head 24}\end{bmatrix} \times 18$
stage 4	32× (7×7)	concat 2×2, 768-d , LN	concat 2×2, 768-d , LN	concat 2×2, 1024-d , LN	concat 2×2, 1536-d , LN
		$\begin{bmatrix}\text{win. sz. } 7\times7,\\ \text{dim 768, head 24}\end{bmatrix} \times 2$	$\begin{bmatrix}\text{win. sz. } 7\times7,\\ \text{dim 768, head 24}\end{bmatrix} \times 2$	$\begin{bmatrix}\text{win. sz. } 7\times7,\\ \text{dim 1024, head 32}\end{bmatrix} \times 2$	$\begin{bmatrix}\text{win. sz. } 7\times7,\\ \text{dim 1536, head 48}\end{bmatrix} \times 2$

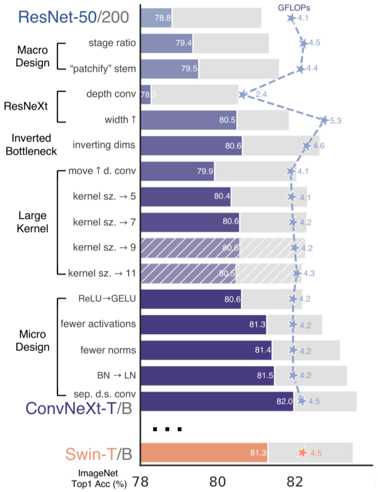
Swin Transformer

(a) Regular ImageNet-1K trained models					
method	image size	#param.	FLOPs	throughput (image / s)	ImageNet top-1 acc.
RegNetY-4G [48]	224^2	21M	4.0G	1156.7	80.0
RegNetY-8G [48]	224^2	39M	8.0G	591.6	81.7
RegNetY-16G [48]	224^2	84M	16.0G	334.7	82.9
EffNet-B3 [58]	300^2	12M	1.8G	732.1	81.6
EffNet-B4 [58]	380^2	19M	4.2G	349.4	82.9
EffNet-B5 [58]	456^2	30M	9.9G	169.1	83.6
EffNet-B6 [58]	528^2	43M	19.0G	96.9	84.0
EffNet-B7 [58]	600^2	66M	37.0G	55.1	84.3
ViT-B/16 [20]	384^2	86M	55.4G	85.9	77.9
ViT-L/16 [20]	384^2	307M	190.7G	27.3	76.5
DeiT-S [63]	224^2	22M	4.6G	940.4	79.8
DeiT-B [63]	224^2	86M	17.5G	292.3	81.8
DeiT-B [63]	384^2	86M	55.4G	85.9	83.1
Swin-T	224^2	29M	4.5G	755.2	81.3
Swin-S	224^2	50M	8.7G	436.9	83.0
Swin-B	224^2	88M	15.4G	278.1	83.5
Swin-B	384^2	88M	47.0G	84.7	84.5

Outline

1. Vision Transformer
2. Swin Transformer
3. ConvNeXt
4. MobileNetV4

ConvNeXt



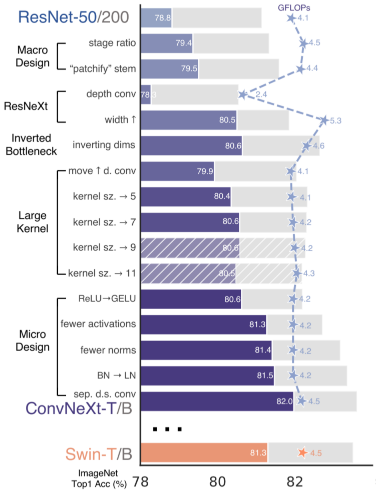
Liu et al. A ConvNet for the 2020s. CVPR 2022

Baseline ResNet-50 with modern training:

- 90 → 300 epochs
- AdamW optimizer
- Augmentations: Mixup, Cutmix, RandAugment, Random Erasing
- Regulatization: Stoch. Depth, Label Smoothing

76.1% → 78.8% on ImageNet

ConvNeXt



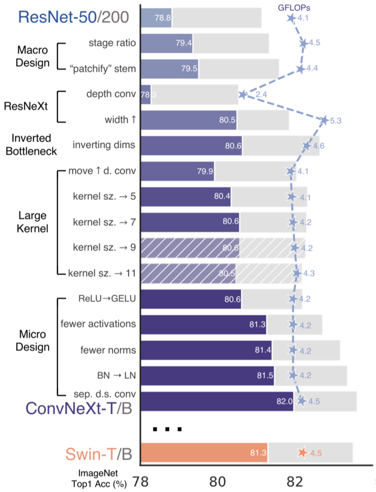
Liu et al. A ConvNet for the 2020s. CVPR 2022

Macro design

Change #blocks
(3,4,6,3) → (3,3,9,3)

Change "patchify" stem
7×7 conv/2, pool/2 → 4×4 conv/4

ConvNeXt



Inverted bottleneck

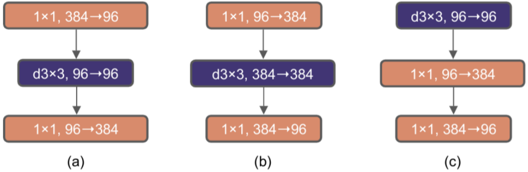
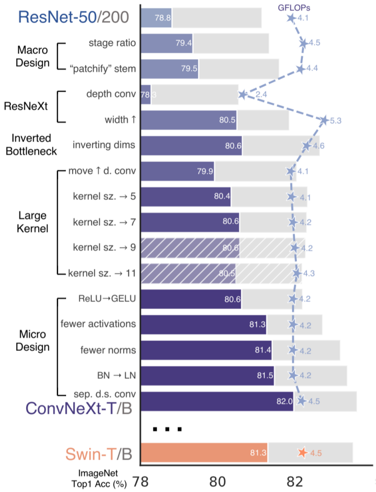


Figure 3. **Block modifications and resulted specifications. (a)** is a ResNeXt block; in **(b)** we create an inverted bottleneck block and in **(c)** the position of the spatial depthwise conv layer is moved up.

Liu et al. A ConvNet for the 2020s. CVPR 2022

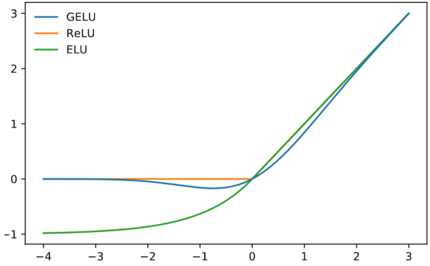
ConvNeXt



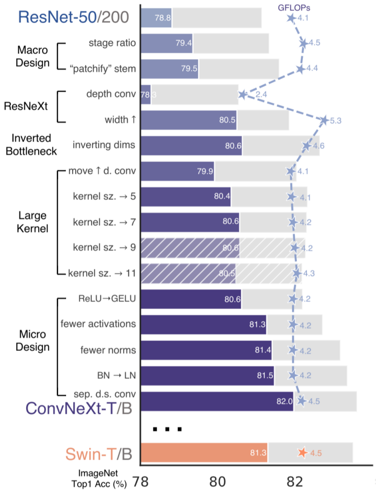
Liu et al. A ConvNet for the 2020s. CVPR 2022

ReLU → GELU

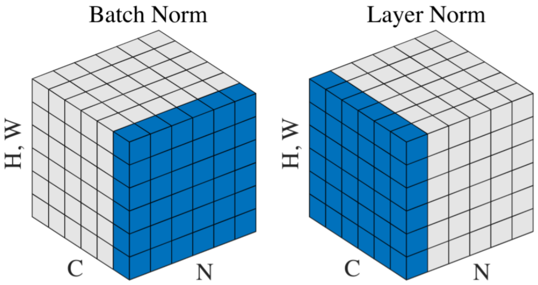
$$GELU(x) = x\Phi(x)$$



ConvNeXt



BatchNorm → LayerNorm



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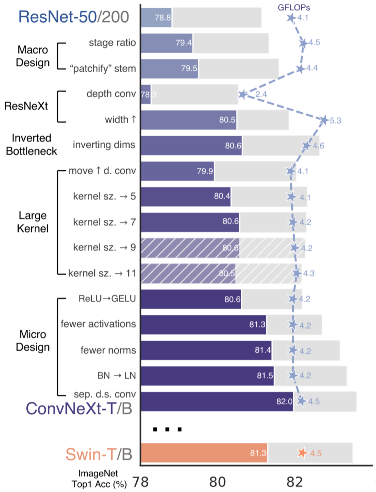
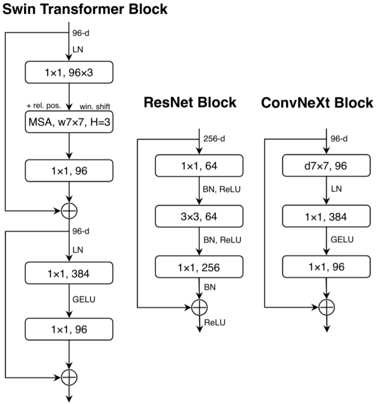
ConvNeXt



Block design



Liu et al. A ConvNet for the 2020s. CVPR 2022

ConvNeXt results

model	image size	#param.	FLOPs	throughput (image / s)	IN-1K top-1 acc.
ImageNet-1K trained models					
● RegNetY-16G [54]	224^2	84M	16.0G	334.7	82.9
● EffNet-B7 [71]	600^2	66M	37.0G	55.1	84.3
● EffNetV2-L [72]	480^2	120M	53.0G	83.7	85.7
○ DeiT-S [73]	224^2	22M	4.6G	978.5	79.8
○ DeiT-B [73]	224^2	87M	17.6G	302.1	81.8
○ Swin-T	224^2	28M	4.5G	757.9	81.3
● ConvNeXt-T	224^2	29M	4.5G	774.7	**82.1**
○ Swin-S	224^2	50M	8.7G	436.7	83.0
● ConvNeXt-S	224^2	50M	8.7G	447.1	**83.1**
○ Swin-B	224^2	88M	15.4G	286.6	83.5
● ConvNeXt-B	224^2	89M	15.4G	292.1	**83.8**
○ Swin-B	384^2	88M	47.1G	85.1	84.5
● ConvNeXt-B	384^2	89M	45.0G	95.7	**85.1**
● ConvNeXt-L	224^2	198M	34.4G	146.8	**84.3**
● ConvNeXt-L	384^2	198M	101.0G	50.4	**85.5**
ImageNet-22K pre-trained models					
● R-101x3 [39]	384^2	388M	204.6G	-	84.4
● R-152x4 [39]	480^2	937M	840.5G	-	85.4
● EffNetV2-L [72]	480^2	120M	53.0G	83.7	86.8
● EffNetV2-XL [72]	480^2	208M	94.0G	56.5	87.3
○ ViT-B/16 (☎) [67]	384^2	87M	55.5G	93.1	85.4
○ ViT-L/16 (☎) [67]	384^2	305M	191.1G	28.5	86.8
● ConvNeXt-T	224^2	29M	4.5G	774.7	**82.9**
● ConvNeXt-T	384^2	29M	13.1G	282.8	**84.1**
● ConvNeXt-S	224^2	50M	8.7G	447.1	**84.6**
● ConvNeXt-S	384^2	50M	25.5G	163.5	**85.8**
○ Swin-B	224^2	88M	15.4G	286.6	85.2
● ConvNeXt-B	224^2	89M	15.4G	292.1	**85.8**
○ Swin-B	384^2	88M	47.0G	85.1	86.4
● ConvNeXt-B	384^2	89M	45.1G	95.7	**86.8**
○ Swin-L	224^2	197M	34.5G	145.0	86.3
● ConvNeXt-L	224^2	198M	34.4G	146.8	**86.6**
○ Swin-L	384^2	197M	103.9G	46.0	87.3
● ConvNeXt-L	384^2	198M	101.0G	50.4	**87.5**
● ConvNeXt-XL	224^2	350M	60.9G	89.3	**87.0**
● ConvNeXt-XL	384^2	350M	179.0G	30.2	**87.8**

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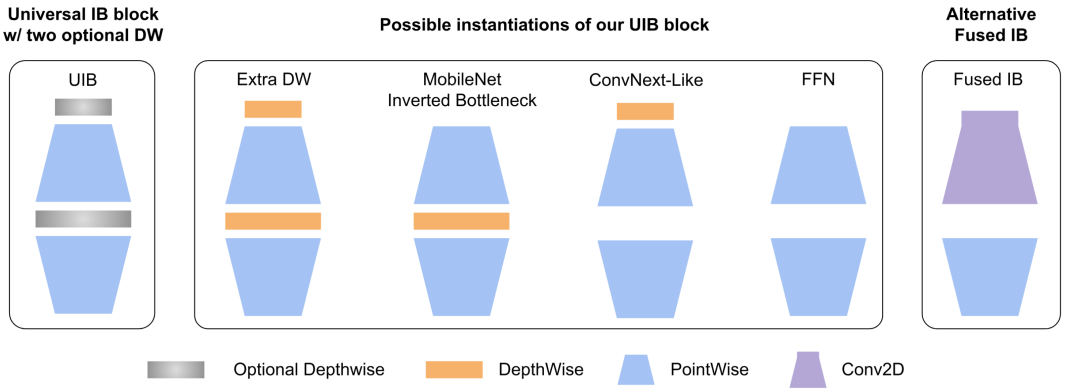
4. MobileNetV4

Universal Inverted Bottleneck



Qin et al. MobileNetV4 — Universal Models for the Mobile Ecosystem. arXiv:2404.10518

Mobile MQA

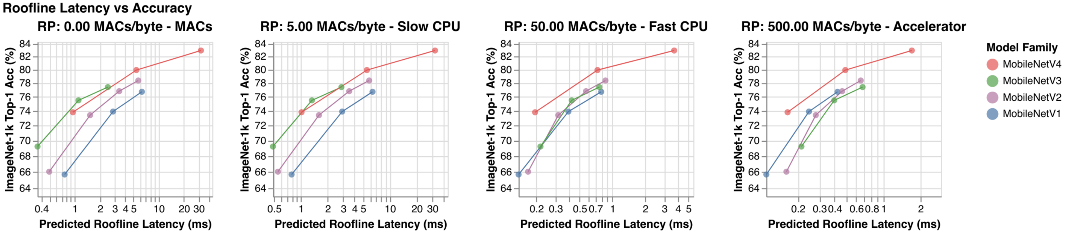
$$\text{Mobile\_MQA}(\mathbf{X}) = \text{Concat}(\text{attention}_1, \ldots, \text{attention}_n)\mathbf{W}^O$$

$$\text{where attention}_j = \text{softmax}\left(\frac{(\mathbf{X}\mathbf{W}^{Q_j})(SR(\mathbf{X})\mathbf{W}^K)^T}{\sqrt{d_k}}\right)(SR(\mathbf{X})\mathbf{W}^V)$$

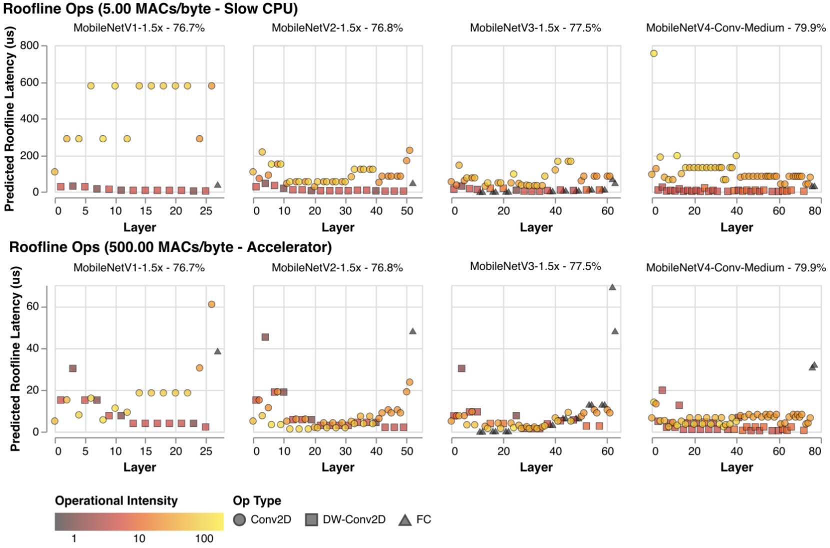
Roofline analysis

$$\text{ModelTime} = \sum_i \max(\text{MACTime}_i, \text{MemTime}_i)$$

$$\text{MACTime}_i = \frac{\text{LayerMACs}_i}{\text{PeakMACs}}, \quad \text{MemTime}_i = \frac{\text{WeightBytes}_i + \text{ActivationBytes}_i}{\text{PeakMemBW}}$$

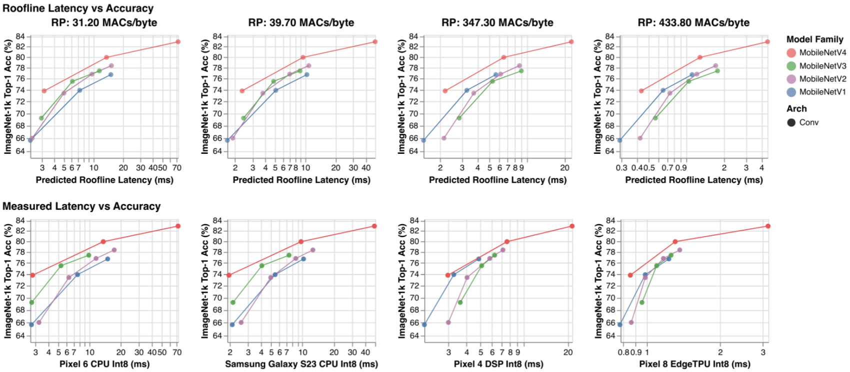


Roofline analysis



Roofline analysis

Execution Target	Ridge Point (MACs/B)	r_s-Roofline	r_s-MAC
Pixel 6 CPU (Int8)	31.2	0.973	0.962
Samsung Galaxy S23 CPU (Int8)	39.7	0.962	0.940
Pixel 4 DSP (Int8)	347.3	0.962	0.758
Pixel 8 EdgeTPU (Int8)	433.8	0.973	0.857



Found architectures

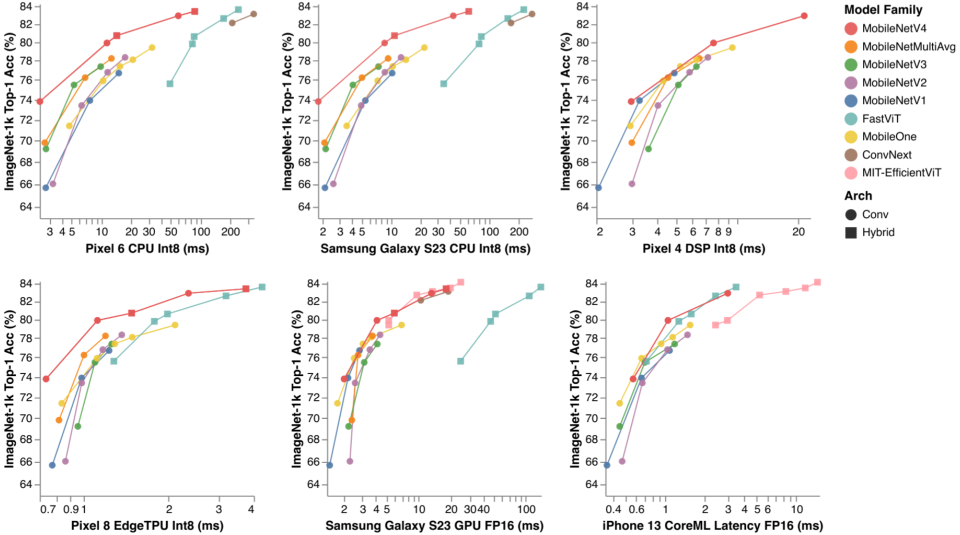
Table 12: Architecture specification of MNv4-Conv-M.

Input	Block	DW K_1	DW K_2	Expanded Dim	Output Dim	Stride
$256^2 \times 3$	Conv2D	-	3×3	-	32	2
$128^2 \times 32$	FusedIB	-	3×3	128	48	2
$64^2 \times 48$	ExtraDW	3×3	5×5	192	80	2
$32^2 \times 80$	ExtraDW	3×3	3×3	160	80	1
$32^2 \times 80$	ExtraDW	3×3	5×5	480	160	2
$16^2 \times 160$	ExtraDW	3×3	3×3	640	160	1
$16^2 \times 160$	ExtraDW	3×3	3×3	640	160	1
$16^2 \times 160$	ExtraDW	3×3	5×5	640	160	1
$16^2 \times 160$	ExtraDW	3×3	3×3	640	160	1
$16^2 \times 160$	ConvNext	3×3	-	640	160	1
$16^2 \times 160$	FFN	-	-	320	160	1
$16^2 \times 160$	ConvNext	3×3	-	640	160	1
$16^2 \times 160$	ExtraDW	5×5	5×5	960	256	2
$8^2 \times 256$	ExtraDW	5×5	5×5	1024	256	1
$8^2 \times 256$	ExtraDW	3×3	5×5	1024	256	1
$8^2 \times 256$	ExtraDW	3×3	5×5	1024	256	1
$8^2 \times 256$	FFN	-	-	1024	256	1
$8^2 \times 256$	ConvNext	3×3	-	1024	256	1
$8^2 \times 256$	ExtraDW	3×3	5×5	512	256	1
$8^2 \times 256$	ExtraDW	5×5	5×5	1024	256	1
$8^2 \times 256$	FFN	-	-	1024	256	1
$8^2 \times 256$	FFN	-	-	1024	256	1
$8^2 \times 256$	ConvNext	5×5	-	512	256	1
$8^2 \times 256$	Conv2D	-	1×1	-	960	1
$8^2 \times 960$	AvgPool	-	8×8	-	960	1
$1^2 \times 960$	Conv2D	-	1×1	-	1280	1
$1^2 \times 1280$	Conv2D	-	1×1	-	1000	1

Table 13: Architecture specification of MNv4-Hybrid-M.

Input	Block	DW K_1	DW K_2	Expanded Dim	Output Dim	Stride
$256^2 \times 3$	Conv2D	-	3×3	-	32	2
$128^2 \times 32$	FusedIB	-	3×3	128	48	2
$64^2 \times 48$	ExtraDW	3×3	5×5	192	80	2
$32^2 \times 80$	ExtraDW	3×3	3×3	160	80	1
$32^2 \times 80$	ExtraDW	3×3	5×5	480	160	2
$16^2 \times 160$	ExtraDW	3×3	3×3	640	160	1
$16^2 \times 160$	ExtraDW	3×3	3×3	640	160	1
$16^2 \times 160$	ExtraDW	3×3	5×5	640	160	1
$16^2 \times 160$	Mobile-MQA	-	-	-	160	1
$16^2 \times 160$	ExtraDW	3×3	3×3	640	160	1
$16^2 \times 160$	Mobile-MQA	-	-	-	160	1
$16^2 \times 160$	ConvNext	3×3	-	640	160	1
$16^2 \times 160$	Mobile-MQA	-	-	-	160	1
$16^2 \times 160$	FFN	-	-	640	160	1
$16^2 \times 160$	Mobile-MQA	-	-	-	160	1
$16^2 \times 160$	ConvNext	3×3	-	640	160	1
$16^2 \times 160$	ExtraDW	5×5	5×5	960	256	2
$8^2 \times 256$	ExtraDW	5×5	5×5	1024	256	1
$8^2 \times 256$	ExtraDW	3×3	5×5	1024	256	1
$8^2 \times 256$	ExtraDW	3×3	5×5	1024	256	1
$8^2 \times 256$	FFN	-	-	1024	256	1
$8^2 \times 256$	ConvNext	3×3	-	1024	256	1
$8^2 \times 256$	ExtraDW	3×3	5×5	512	256	1
$8^2 \times 256$	Mobile-MQA	-	-	-	256	1
$8^2 \times 256$	ExtraDW	5×5	5×5	1024	256	1
$8^2 \times 256$	Mobile-MQA	-	-	-	256	1
$8^2 \times 256$	FFN	-	-	1024	256	1
$8^2 \times 256$	Mobile-MQA	-	-	-	256	1
$8^2 \times 256$	FFN	-	-	1024	256	1
$8^2 \times 256$	Mobile-MQA	-	-	-	256	1
$8^2 \times 256$	ConvNext	5×5	-	1024	256	1
$8^2 \times 256$	Conv2D	-	1×1	-	960	1
$8^2 \times 960$	AvgPool	-	8×8	-	960	1
$1^2 \times 960$	Conv2D	-	1×1	-	1280	1
$1^2 \times 1280$	Conv2D	-	1×1	-	1000	1

Evaluation results



Conclusion

We reviewed three key modern backbones:

1. Vision Transformer (ViT) applies ideas from NLP to images. Key element is attention — mechanism for gathering information across whole image
2. Swin Transformer reintroduces convnet priors to transformers using shifted window attention
3. ConvNeXt modernizes ResNets into a transformer-like fully convolutional architecture
4. MobileNetV4 combines ideas from CNNs and transformers and uses NAS and Roofline Analysis to find fast architectures that works well across various devices