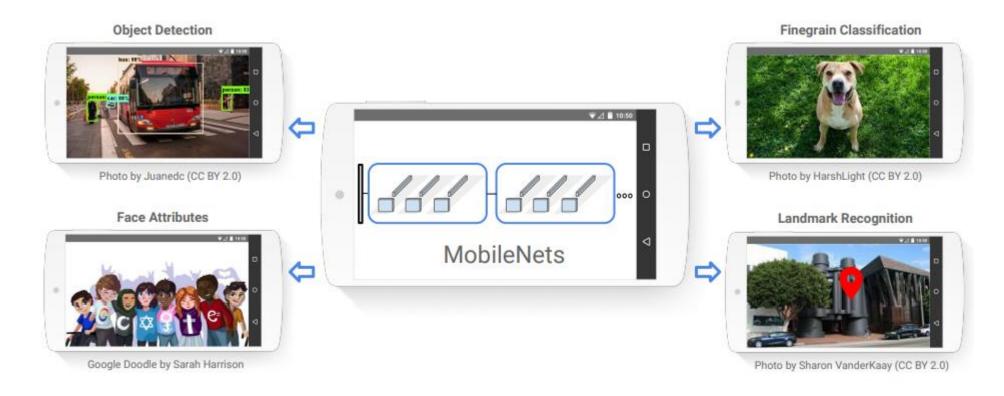
• 연구동기:

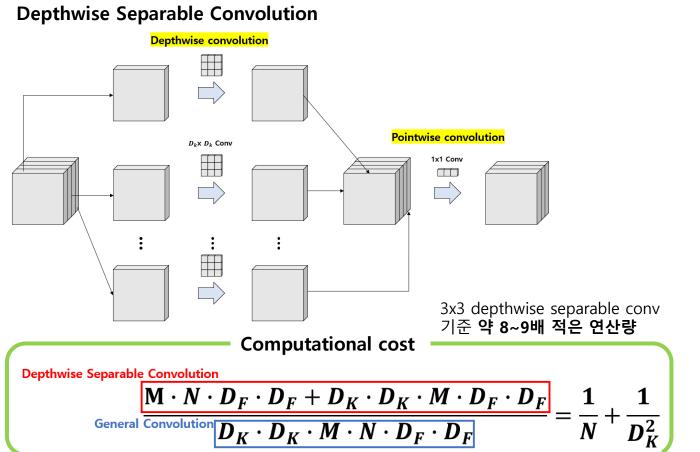
휴대폰이나 임베디드 시스템같은 저용량 메모리 환경에 딥러닝 적용을 위한 **모델 경량화** 필수. Depthwise Separable Convolution을 사용한 MobileNet 제안.

Application 환경에 따른 적절한 설계를 위한 2개의 hyperparameter(width multiplier, resolution multiplier) -> latency, accuracy 균형 조절

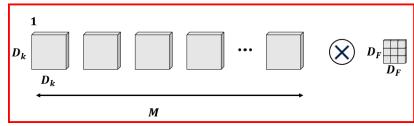


Method:

모델의 첫 번째 layer를 제외하고 모두 depthwise separable convolution으로 변경해 적용. **Depthwise convolution** + **Pointwise convolution** => 연산량↓+ 모델 크기↓

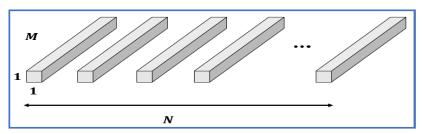


Depthwise Convolution $(D_K \cdot D_K \cdot M \cdot D_F \cdot D_F)$





Pointwise Convolution $(M \cdot N \cdot D_F \cdot D_F)$



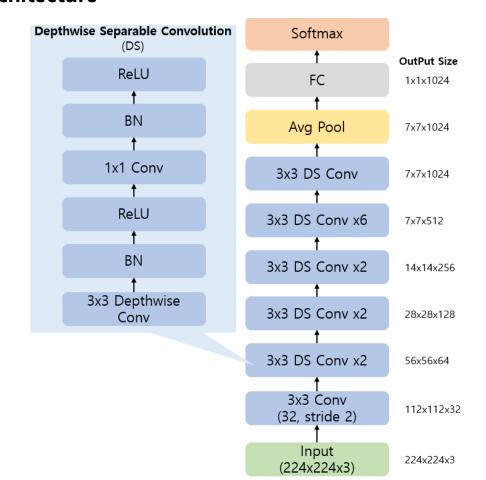
Method:

모델의 첫 번째 layer를 제외하고 모두 depthwise separable convolution으로 변경해 적용.

MobileNet Architecture

Table 1.	. MobileNet	Body A	Architecture
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Table 1: Woohlervet Body Artemicecture							
Type / Stride	Filter Shape	Input Size					
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$					
Conv dw / s1	$3 \times 3 \times 32 \text{ dw}$	$112 \times 112 \times 32$					
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$					
Conv dw / s2	$3 \times 3 \times 64 \text{ dw}$	$112 \times 112 \times 64$					
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$					
Conv dw / s1	$3 \times 3 \times 128 \text{ dw}$	$56 \times 56 \times 128$					
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$					
Conv dw / s2	$3 \times 3 \times 128 \text{ dw}$	$56 \times 56 \times 128$					
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$					
Conv dw / s1	$3 \times 3 \times 256 \text{ dw}$	$28 \times 28 \times 256$					
Conv / s1	$1\times1\times256\times256$	$28 \times 28 \times 256$					
Conv dw / s2	$3 \times 3 \times 256 \text{ dw}$	$28 \times 28 \times 256$					
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$					
5× Conv dw / s1	$3 \times 3 \times 512 \text{ dw}$	$14 \times 14 \times 512$					
Conv / s1	$1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$					
Conv dw / s2	$3 \times 3 \times 512 \text{ dw}$	$14 \times 14 \times 512$					
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$					
Conv dw / s2	$3 \times 3 \times 1024 \text{ dw}$	$7 \times 7 \times 1024$					
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$					
Avg Pool / s1	Pool 7 × 7	$7 \times 7 \times 1024$					
FC / s1	1024×1000	$1 \times 1 \times 1024$					
Softmax / s1	Classifier	$1 \times 1 \times 1000$					



• Method: 2개의 hyperparameter (width multiplier, resolution multiplier) -> latency, accuracy 균형 조절

Width Multiplier (α) : Thinner Models 네트워크를 균일하게 **얇게** 만든다.

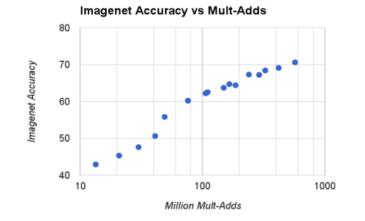
Computational cost using Width Multiplier (α) $\alpha M \cdot \alpha N \cdot D_F \cdot D_F + D_K \cdot D_K \cdot \alpha M \cdot D_F \cdot D_F$ $\alpha \in (0, 1), \alpha = (1, 0.75, 0.5, 0.25)$

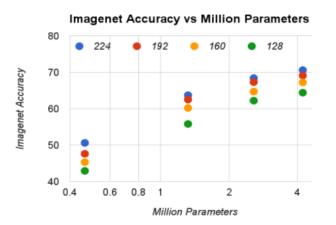
Table 6. MobileNet Width Multiplier							
Width Multiplier	ImageNet	Million	Million				
	Accuracy	Mult-Adds	Parameters				
1.0 MobileNet-224	70.6%	569	4.2				
0.75 MobileNet-224	68.4%	325	2.6				
0.5 MobileNet-224	63.7%	149	1.3				
0.25 MobileNet-224	50.6%	41	0.5				

Resolution Multiplier (ρ): Reduced Representation 신경망의 계산비용 감소.

Computational cost using Resolution Multiplier (ρ) $\alpha M \cdot \alpha N \cdot \rho D_F \cdot \rho D_F + D_K \cdot D_K \cdot \alpha M \cdot \rho D_F \cdot \rho D_F$ $\rho \in (0,1), \ \rho = (224, 192, 160, 128)$

Table 7. MobileNet Resolution							
Resolution	ImageNet	Million	Million				
	Accuracy	Mult-Adds	Parameters				
1.0 MobileNet-224	70.6%	569	4.2				
1.0 MobileNet-192	69.1%	418	4.2				
1.0 MobileNet-160	67.2%	290	4.2				
1.0 MobileNet-128	64.4%	186	4.2				





Experiment:

65.3%

307

Shallow MobileNet

Depthwise separable conv를 사용한 MobileNet이 Fully convolutional MobileNet보다 더 적은 parameter 를 나타내면서 합리적인 정확도를 보인다.

기존의 VGG-16보다 더 적은 parameter 로 비슷한 정확도를 보인다.

AlexNet

기존의 very small network (squeezeNet, AlexNet) 보다 더 좋은 성능을 보인다.

이 외에도 다양한 task에서 성공적인 모델 경량화.

Table 4. Depthwise Separable vs Full Convolution MobileNet			Table 8. MobileNet Comparison to Popular Models			Table 10. MobileNet for Stanford Dogs					
Model	ImageNet	Million	Million	Model	ImageNet	Million	Million	Model	Top-1	Million	Million
	Accuracy	Mult-Adds	Parameters		Accuracy	Mult-Adds	Parameters		Accuracy	Mult-Adds	Parameters
Conv MobileNet	71.7%	4866	29.3	1.0 MobileNet-224	70.6%	569	4.2	Inception V3 [18]	84%	5000	23.2
MobileNet	70.6%	569	4.2	GoogleNet	69.8%	1550	6.8	1.0 MobileNet-224	83.3%	569	3.3
_Better Performance				VGG 16	71.5%	15300	138	0.75 MobileNet-224	81.9%	325	1.9
Table 5. Narrow vs Shallow MobileNet					. 3.6 . 1.1	1.0 MobileNet-192	81.9%	418	3.3		
Model	ImageNet	Million	Million	Table 9. Smaller Mobil	eNet Compar	ison to Popula		0.75 MobileNet-192	80.5%	239	1.9
Better Performance	Accuracy	Mult-Adds	Parameters	Model	ImageNet	Million	Million	0.75 Modificact-192	00.5%	239	1.9
0.75 MobileNet	68.4%	325	2.6		Accuracy	Mult-Adds	Parameters				
Shallow MobileNet		307	2.9	0.50 MobileNet-160	60.2%	76	1.32	•			

1700

720

1.25 60

57.5%

57.2%