

# ResNet 디자인



layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
		3×3 max pool, stride 2				
conv2_x	56×56	$\begin{bmatrix} 3 \times 3, 64 \\ 3 \times 3, 64 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, 64 \\ 3 \times 3, 64 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$ stride=1
conv3_x	28×28	$\begin{bmatrix} 3 \times 3, 128 \\ 3 \times 3, 128 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, 128 \\ 3 \times 3, 128 \end{bmatrix} \times 4$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 8$ stride=2
conv4_x	14×14	$\begin{bmatrix} 3 \times 3, 256 \\ 3 \times 3, 256 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, 256 \\ 3 \times 3, 256 \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 23$	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 36$ stride=2
conv5_x	7×7	$\begin{bmatrix} 3 \times 3, 512 \\ 3 \times 3, 512 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, 512 \\ 3 \times 3, 512 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$ stride=2
	1×1	average pool, 1000-d fc				
FLOPs		$1.8 \times 10^9$	$3.6 \times 10^9$	$3.8 \times 10^9$		

$$\begin{aligned}
 64 * 4 &= 256 \\
 128 * 4 &= 512 \\
 512 * 4 &= 2048
 \end{aligned}$$

Table 1. Architectures for ImageNet. Building blocks are shown in brackets (see a sampling is performed by conv3\_1, conv4\_1, and conv5\_1 with a stride of 2.

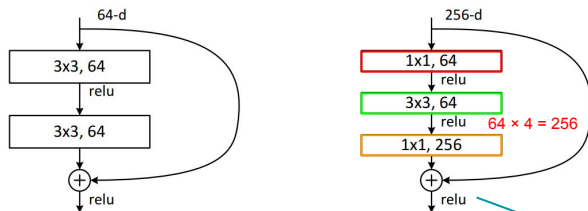


Figure 5. A deeper residual function  $\mathcal{F}$  for ImageNet. Left: a building block (on  $56 \times 56$  feature maps) as in Fig. 3 for ResNet-34. Right: a “bottleneck” building block for ResNet-50/101/152.

```

8  ## residual block 정의
9  class block(nn.Module):
10     def __init__(
11         self, in_channels, out_channels, identity_downsample=None, stride=1):
12         super(block, self).__init__() # 상속받은 부모 클래스의 모든 attributes를 그대로 받아옴
13         self.expansion = 4
14
15         self.conv1 = nn.Conv2d( in_channels=in_channels, out_channels=out_channels, kernel_size=1, stride=1, padding=0 )
16         self.bn1 = nn.BatchNorm2d(out_channels)
17         self.conv2 = nn.Conv2d( out_channels, out_channels, kernel_size=3, stride=stride, padding=1)
18         self.bn2 = nn.BatchNorm2d(out_channels)
19         self.conv3 = nn.Conv2d( out_channels, out_channels * self.expansion, kernel_size=1, stride=1, padding=0 )
20         self.bn3 = nn.BatchNorm2d(out_channels * self.expansion)
21         self.relu = nn.ReLU()
22         self.identity_downsample = identity_downsample
23
24     def forward(self, x):
25         identity = x.clone() # identity_value 저장
26
27         x = self.conv1(x)
28         x = self.bn1(x)
29         x = self.relu(x)
30         x = self.conv2(x)
31         x = self.bn2(x)
32         x = self.relu(x)
33         x = self.conv3(x)
34         x = self.bn3(x)
35
36         if self.identity_downsample is not None:
37             identity = self.identity_downsample(identity)
38
39         x += identity
40         x = self.relu(x)
41         return x

```

out\_channels \* 4

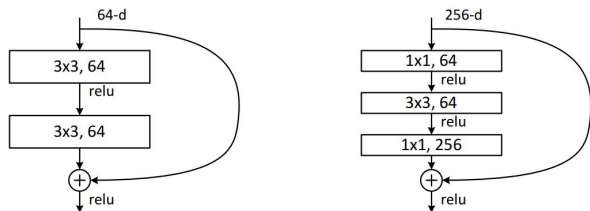
layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
		3×3 max pool, stride 2				
conv2_x	56×56	$\begin{bmatrix} 3 \times 3, 64 \\ 3 \times 3, 64 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, 64 \\ 3 \times 3, 64 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$
conv3_x	28×28	$\begin{bmatrix} 3 \times 3, 128 \\ 3 \times 3, 128 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, 128 \\ 3 \times 3, 128 \end{bmatrix} \times 4$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1 \times 1, 128 \end{bmatrix}$	$\begin{bmatrix} 1 \times 1, 128 \end{bmatrix}$
conv4_x	14×14	$\begin{bmatrix} 3 \times 3, 256 \\ 3 \times 3, 256 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, 256 \\ 3 \times 3, 256 \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1, 256 \end{bmatrix}$	$\begin{bmatrix} 1 \times 1, 256 \end{bmatrix}$
conv5_x	7×7	$\begin{bmatrix} 3 \times 3, 512 \\ 3 \times 3, 512 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, 512 \\ 3 \times 3, 512 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		$1.8 \times 10^9$	$3.6 \times 10^9$	$3.8 \times 10^9$	$7.6 \times 10^9$	$11.3 \times 10^9$

```

47 class ResNet(nn.Module):
48     """ layers := residual_block의 개수를 리스트 형태로 담고 있음
49         (e.g) layers = [3, 4, 6, 3]\
50     """
51     def __init__(self, block, layers, image_channels, num_classes):
52         super(ResNet, self).__init__() # 상속받은 부모 클래스의 모든 attributes를 그대로 받아옴

```

Table 1. Architectures for ImageNet. Building blocks are shown in brackets (see also Fig. 5), with the numbers of blocks stacked. Down-sampling is performed by conv3\_1, conv4\_1, and conv5\_1 with a stride of 2.



```

123 #%% 모델 타입
124 def ResNet50(img_channel=3, num_classes=1000):
125     return ResNet(block, [3, 4, 6, 3], img_channel, num_classes)
126
127
128 def ResNet101(img_channel=3, num_classes=1000):
129     return ResNet(block, [3, 4, 23, 3], img_channel, num_classes)
130
131
132 def ResNet152(img_channel=3, num_classes=1000):
133     return ResNet(block, [3, 8, 36, 3], img_channel, num_classes)

```

Figure 5. A deeper residual function  $\mathcal{F}$  for ImageNet. Left: a building block (on  $56 \times 56$  feature maps) as in Fig. 3 for ResNet-34. Right: a “bottleneck” building block for ResNet-50/101/152.

pad=3 →

layer name	output size	18-layer	34-layer	50-layer	101-layer
conv1	112×112			7×7, 64, stride 2	
				3×3 max pool, stride 2	
conv2_x	56×56	$\begin{bmatrix} 3 \times 3, 64 \\ 3 \times 3, 64 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, 64 \\ 3 \times 3, 64 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix}$
conv3_x	28×28	$\begin{bmatrix} 3 \times 3, 128 \\ 3 \times 3, 128 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, 128 \\ 3 \times 3, 128 \end{bmatrix} \times 4$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix}$
conv4_x	14×14	$\begin{bmatrix} 3 \times 3, 256 \\ 3 \times 3, 256 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, 256 \\ 3 \times 3, 256 \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix}$
conv5_x	7×7	$\begin{bmatrix} 3 \times 3, 512 \\ 3 \times 3, 512 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, 512 \\ 3 \times 3, 512 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix}$
	1×1			average pool, 1000-d fc, softmax	
FLOPs		1.8×10 <sup>9</sup>	3.6×10 <sup>9</sup>	3.8×10 <sup>9</sup>	7.6×10 <sup>9</sup>

Table 1. Architectures for ImageNet. Building blocks are shown in brackets (see also Fig. 5), sampling is performed by conv3\_1, conv4\_1, and conv5\_1 with a stride of 2.

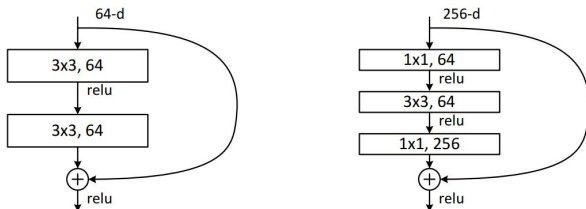


Figure 5. A deeper residual function  $\mathcal{F}$  for ImageNet. Left: a building block (on  $56 \times 56$  feature maps) as in Fig. 3 for ResNet-34. Right: a “bottleneck” building block for ResNet-50/101/152.

```

45 class ResNet(nn.Module):
46     """ layers = residual_block 의 개수를 리스트 형태로 담고 있음
47     (e.g) layers = [3, 4, 6, 3]
48     """
49     def __init__(self, block, layers, image_channels, num_classes):
50         super(ResNet, self).__init__() # 상속받은 부모 클래스의 모든 attributes를 그대로 받음
51
52         *** conv1 정의
53         ***
54         self.in_channels = 64
55         self.conv1 = nn.Conv2d(image_channels, 64, kernel_size=7, stride=2, padding=3)
56         self.bn1 = nn.BatchNorm2d(64)
57         self.relu = nn.ReLU()
58         self.maxpool = nn.MaxPool2d(kernel_size=3, stride=2, padding=1)
59
60
61         *** ResNet layers 정의
62         나머지 conv2_x, conv3_x, conv4_x, conv5_x 정의
63         ***
64         # Essentially the entire ResNet architecture are in these 4 lines below
65         self.layer1 = self.make_layer(block, layers[0], out_channels=64, stride=1)
66         self.layer2 = self.make_layer(block, layers[1], out_channels=128, stride=2)
67         self.layer3 = self.make_layer(block, layers[2], out_channels=256, stride=2)
68         self.layer4 = self.make_layer(block, layers[3], out_channels=512, stride=2)
69
70         *** 마지막 레이어
71         ***
72         self.avgpool = nn.AdaptiveAvgPool2d((1, 1))
73         self.fc = nn.Linear(512 * 4, num_classes)
74
75     def forward(self, x):
76         x = self.conv1(x)
77         x = self.bn1(x)
78         x = self.relu(x)
79         x = self.maxpool(x)
80         x = self.layer1(x)
81         x = self.layer2(x)
82         x = self.layer3(x)
83         x = self.layer4(x)
84
85         x = self.avgpool(x)
86         x = x.reshape(x.shape[0], -1)
87         x = self.fc(x)
88
89         return x
90
91     def make_layer(self, block, num_residual_blocks, out_channels, stride):
92         identity_downsample = None
93         layers = []
94         # Either if we half the input space for ex, 56x56 -> 28x28 (stride=2), or channels changes
95         # we need to adapt the Identity (skip connection) so it will be able to be added
96         # to the layer that's ahead
97         if (stride != 1) or (self.in_channels != out_channels * 4):
98             identity_downsample = nn.Sequential(
99                 nn.Conv2d(self.in_channels, out_channels * 4, kernel_size=1, stride=stride),
100                 nn.BatchNorm2d(out_channels * 4),
101             )
102
103         *** Residual_block 추가
104         ***
105         layers.append(block(self.in_channels, out_channels, identity_downsample, stride))
106
107         # The expansion size is always 4 for ResNet 50,101,152
108         self.in_channels = out_channels * 4
109
110         *** For example for first resnet layer: 256 will be mapped to 64 as intermediate layer,
111         then finally back to 256. Hence no identity downsample is needed, since stride = 1,
112         and also same amount of channels.
113         ***
114         for i in range(num_residual_blocks - 1):
115             layers.append(block(self.in_channels, out_channels))
116
117         return nn.Sequential(*layers)
118

```

ex) ResNet50 일 때  
layers = [3, 4, 6, 3]  
layers[0] := 3

3, 64, 1

64, 64, None, 1