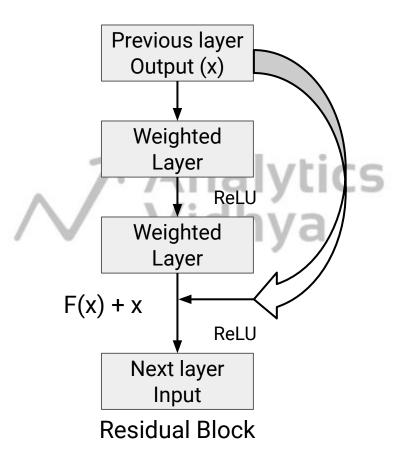
# DenseNet/tics Idnya

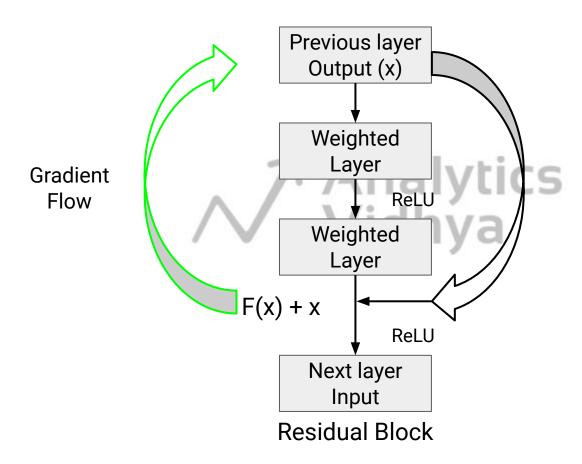


#### ResNet





#### ResNet









#### Proposed in 2018

#### **Densely Connected Convolutional Networks**

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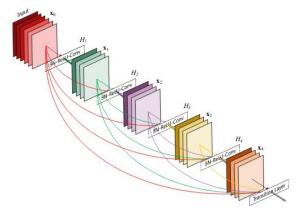
Laurens van der Maaten Facebook AI Research

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#### Abstract

Recent work has shown that convolutional networks can be substantially deeper, more accurate, and efficient to train if they contain shorter connections between layers close to the input and those close to the output. In this paper, we embrace this observation and introduce the Dense Convolutional Network (DenseNet), which connects each layer to every other layer in a feed-forward fashion. Whereas traditional convolutional networks with L layers have L connections—one between each layer and its subsequent layer—our network has  $\frac{L(L+1)}{2}$  direct connections. For each layer, the feature-maps of all preceding layers are used as inputs, and its own feature-maps are used as inputs





- Proposed in 2018
- Architectural details:
  - Mosty 3 X 3 convolutions are used

Analytics Vidhya

- Proposed in 2018
- Architectural details:
  - Mosty 3 X 3 convolutions are used
  - Batch normalization and ReLU used before conv layers in dense blocks

Vidhya



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  - Mosty 3 X 3 convolutions are used
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  - 1 X 1 convolution used to reduce the size of feature map



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  - 1 X 1 convolution used to reduce the size of feature map
- Connects each layer to all the subsequent layer

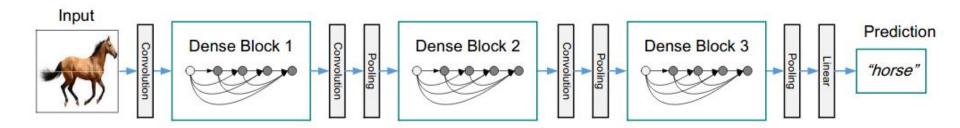


- Proposed in 2018
- Architectural details:
  - Mosty 3 X 3 convolutions are used
  - Batch normalization and ReLU used before conv layers in dense blocks
  - 1 X 1 convolution used to reduce the size of feature map
- Connects each layer to all the subsequent layer
- Do not add features using element-wise addition, instead it concatenates the features

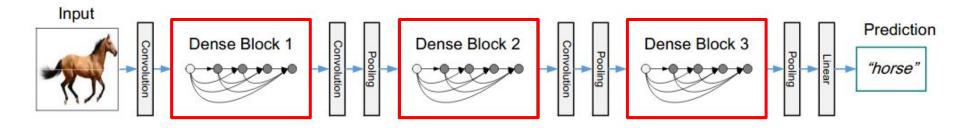




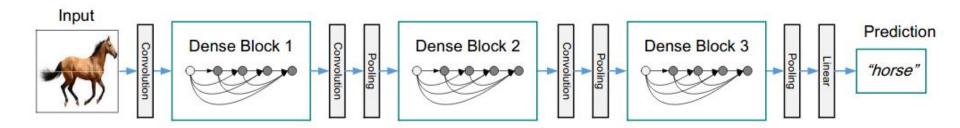




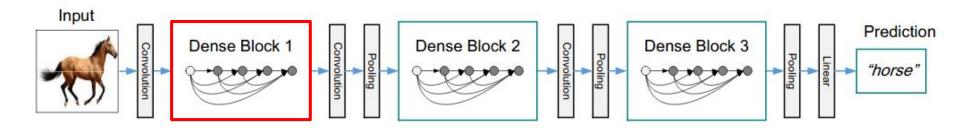






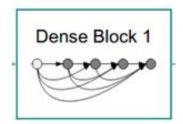








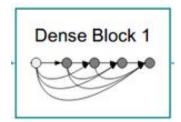






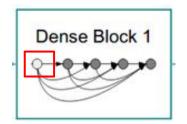
Input (56, 56, 64)





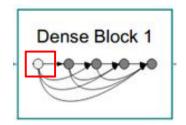




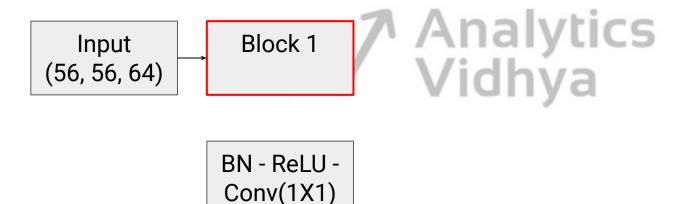












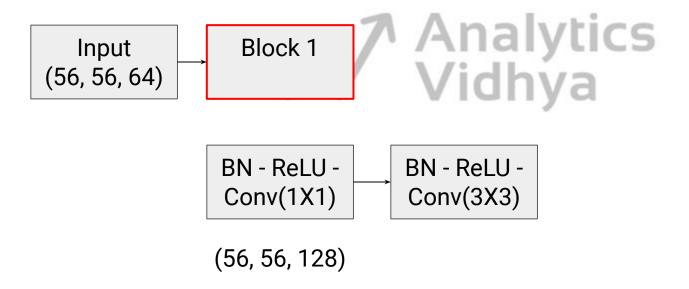




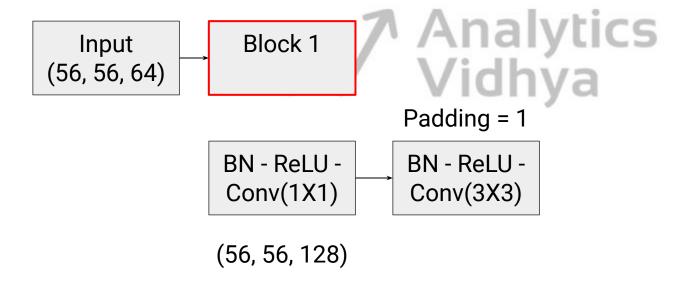
BN - ReLU -Conv(1X1)

(56, 56, 128)

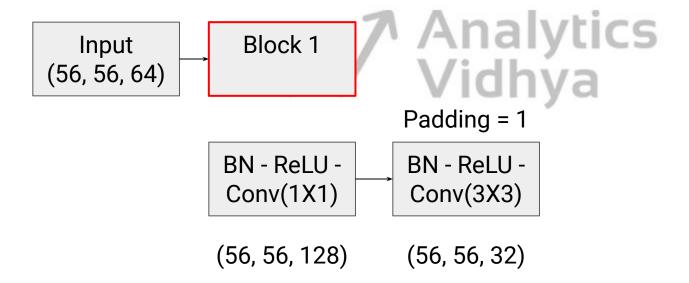






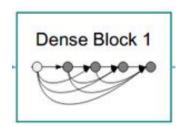




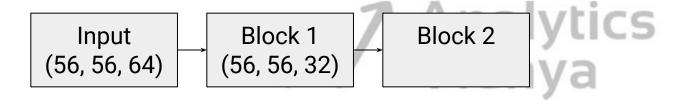


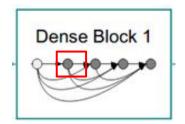




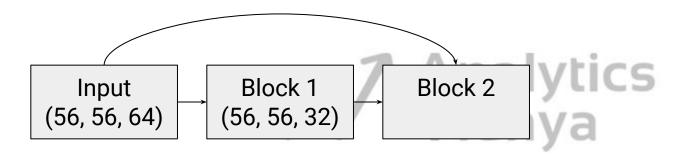


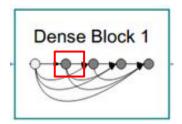




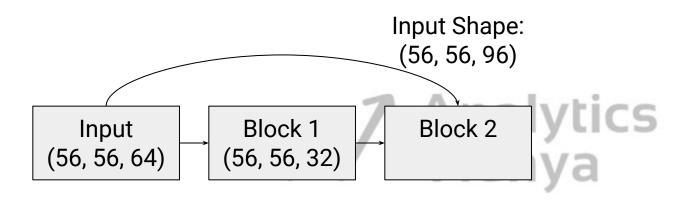


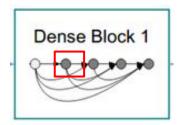




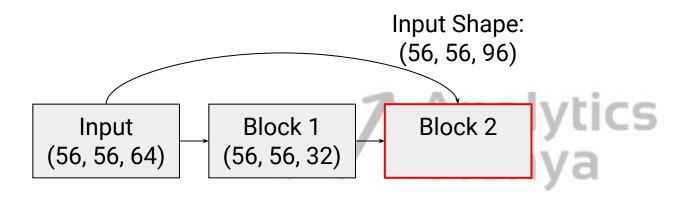


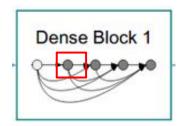




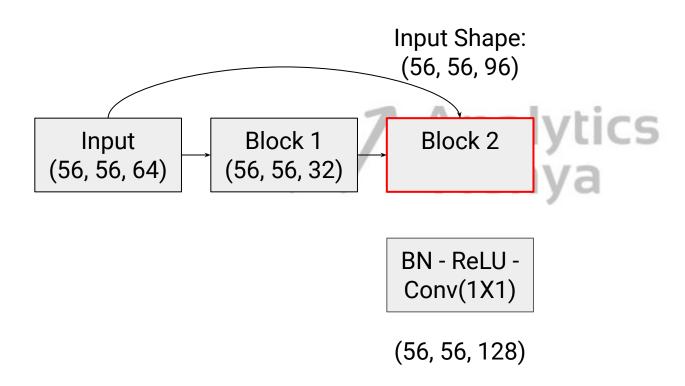




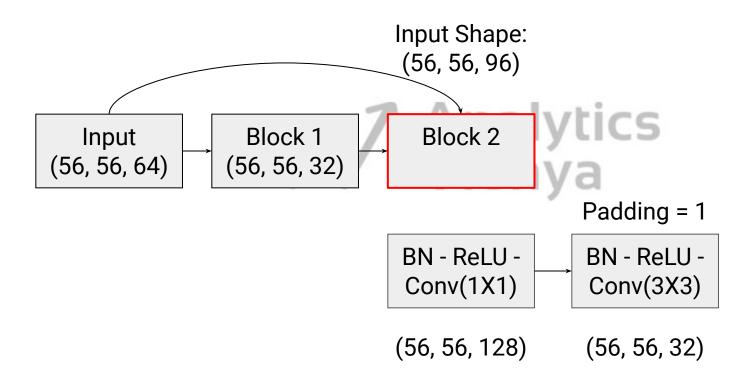




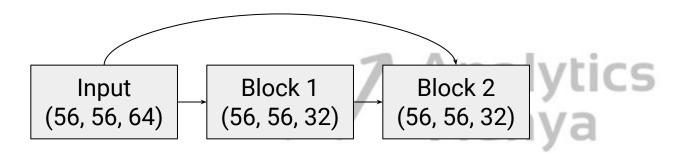


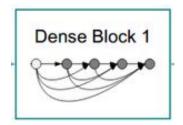




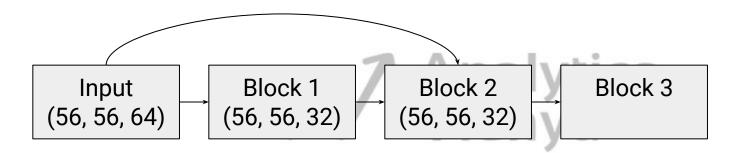


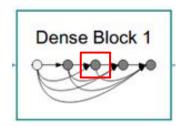




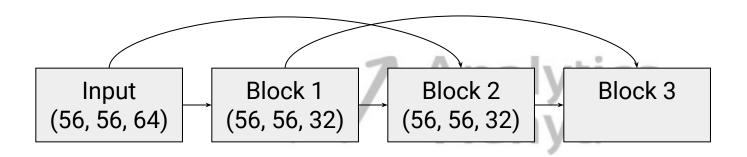


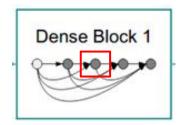




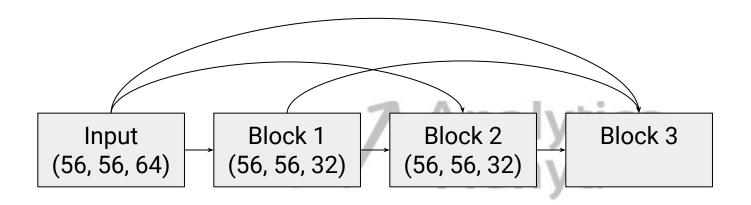


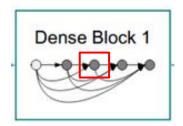




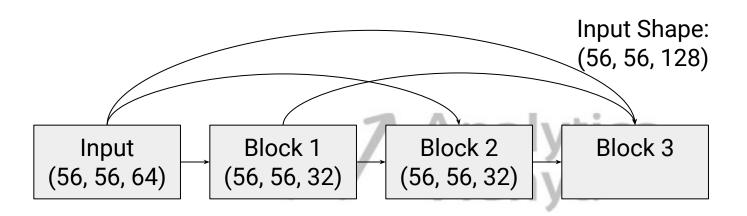


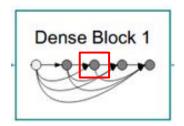






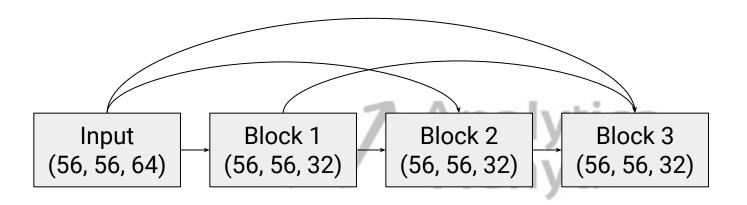


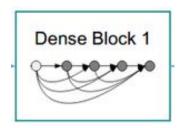






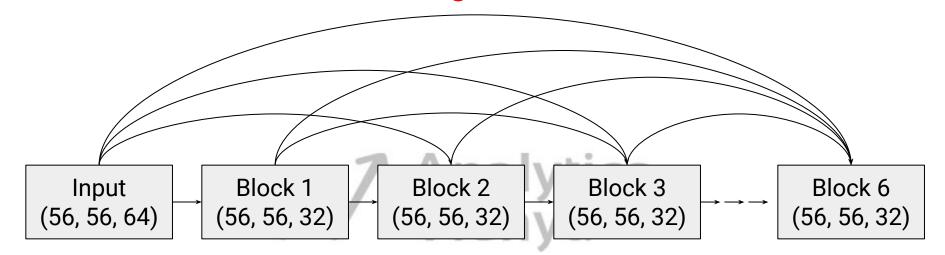
# **Understanding Dense Blocks**



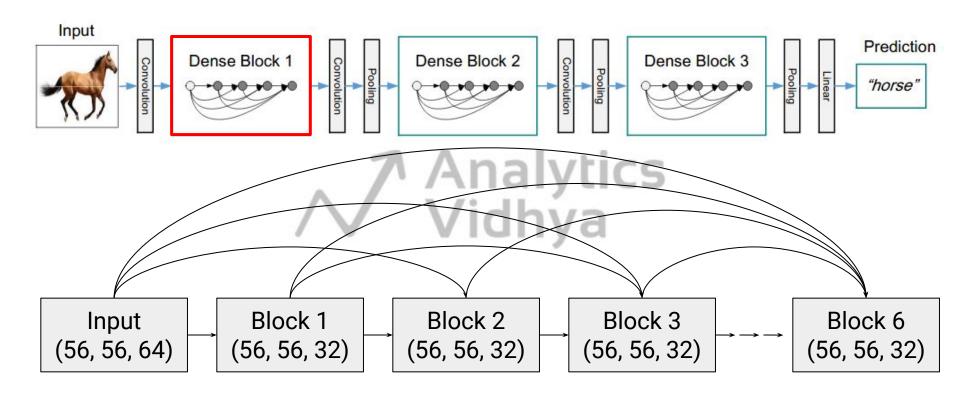




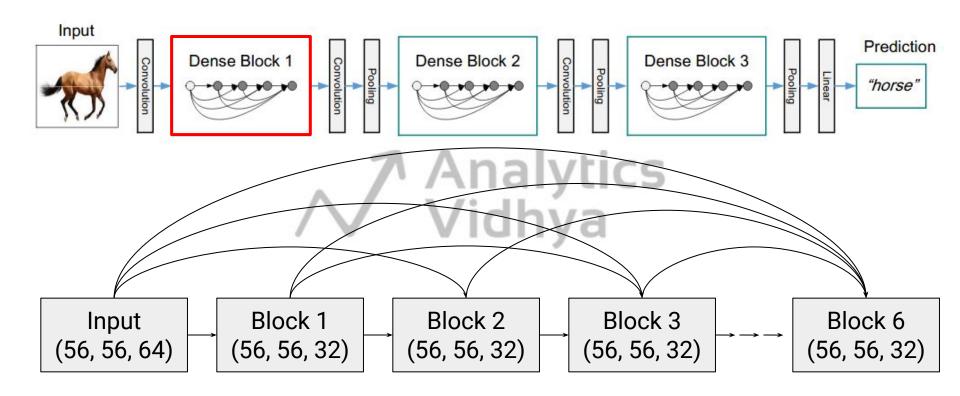
# **Understanding Dense Blocks**





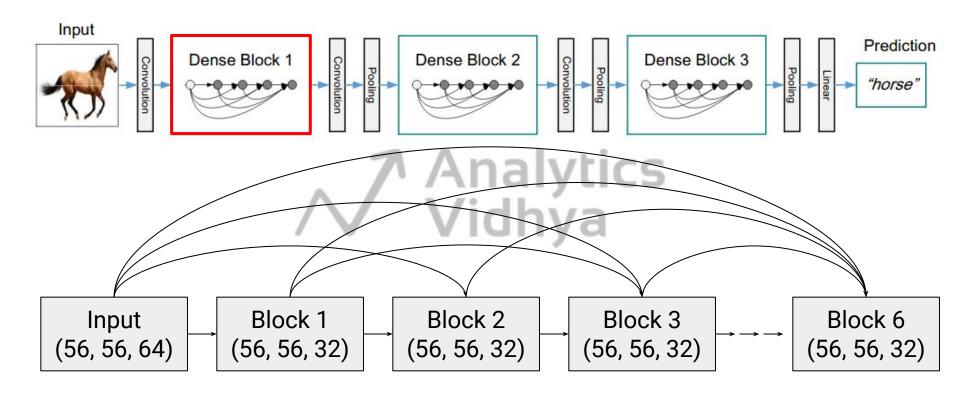






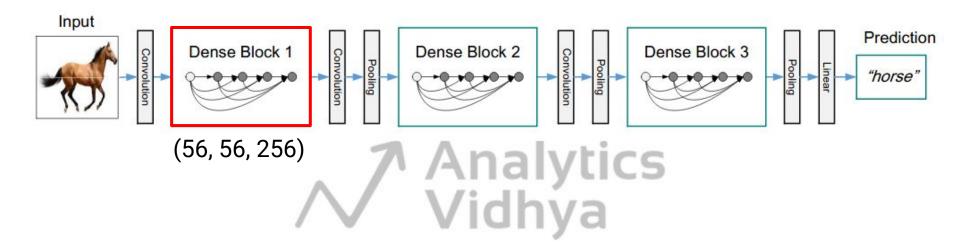
Output shape: (56, 56, 64 + 6\*32)



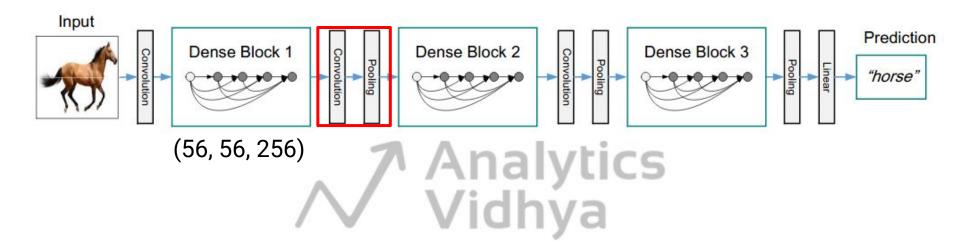


Output shape: (56, 56, 64 + 6\*32) = (56, 56, 256)

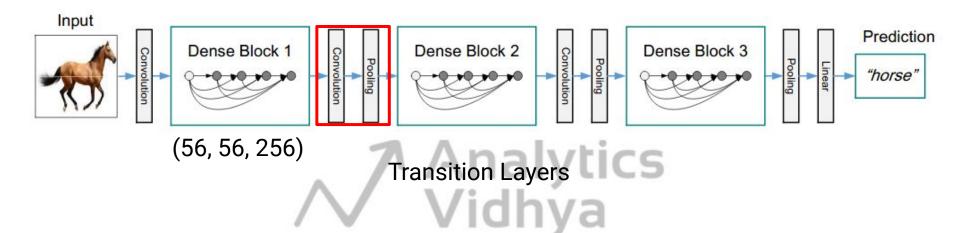




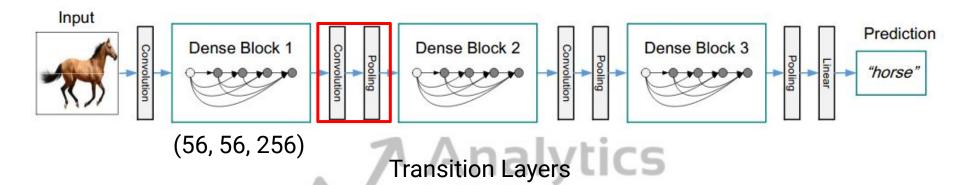








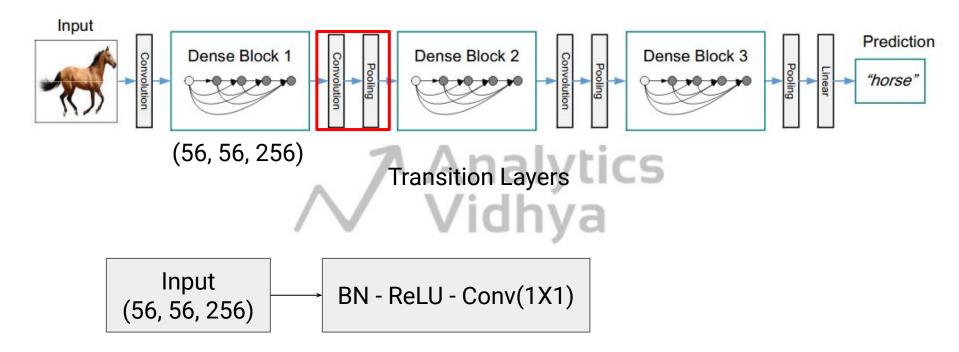




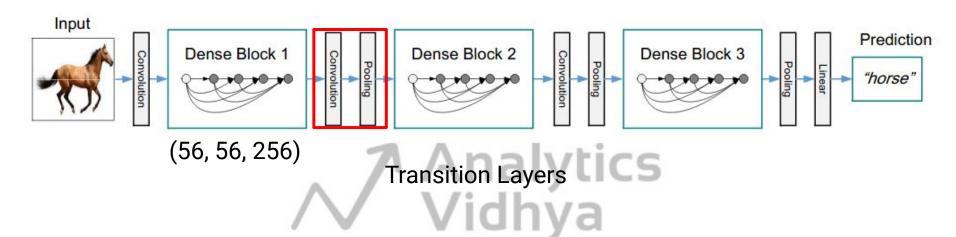
Vidhya

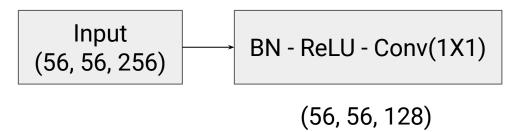
Input (56, 56, 256)



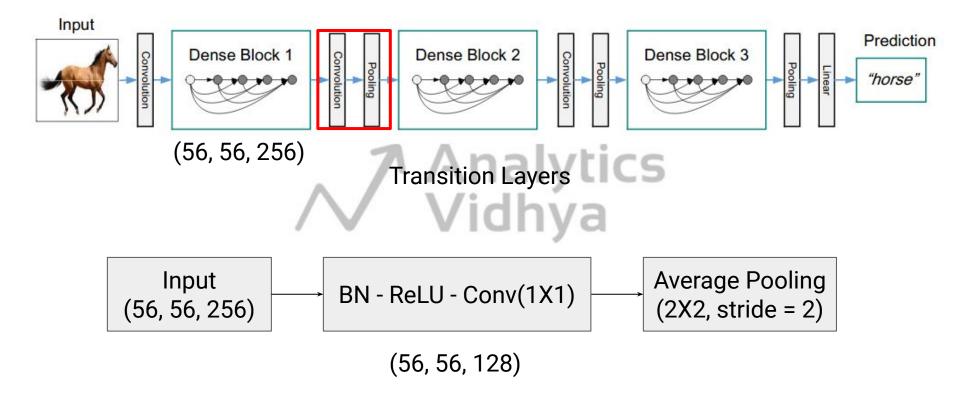




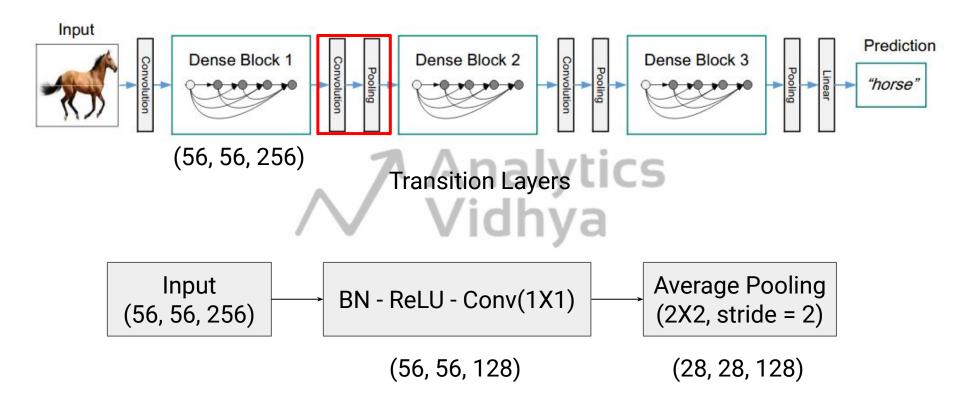














Layers	Output Size	DenseNet-121	DenseNet-169	DenseNet-201	DenseNet-264
Convolution	112 × 112	$7 \times 7$ conv, stride 2			
Pooling	56 × 56	$3 \times 3$ max pool, stride 2			
Dense Block (1)	56 × 56	$\left[\begin{array}{c} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{array}\right] \times 6$	$\left[\begin{array}{c} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{array}\right] \times 6$	$\left[\begin{array}{c} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{array}\right] \times 6$	$\left[\begin{array}{c} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{array}\right] \times 6$
Transition Layer	56 × 56	$1 \times 1 \text{ conv}$			
(1)	28 × 28	2 × 2 average pool, stride 2			
Dense Block (2)	28 × 28	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\left[\begin{array}{c} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{array}\right] \times 12$	$\left[\begin{array}{c} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{array}\right] \times 12$	$\left[\begin{array}{c} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{array}\right] \times 12$
Transition Layer	28 × 28	$1 \times 1 \text{ conv}$			
(2)	14 × 14	$\times$ 14 2 $\times$ 2 average pool, stride 2		e pool, stride 2	
Dense Block (3)	14 × 14	$\left[\begin{array}{c} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{array}\right] \times 24$	$\left[\begin{array}{c} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{array}\right] \times 32$	$\left[\begin{array}{c} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{array}\right] \times 48$	$\left[\begin{array}{c} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{array}\right] \times 64$
Transition Layer	14 × 14	1 × 1 conv			
(3)	7 × 7	2 × 2 average pool, stride 2			
Dense Block (4)	7 × 7	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 16$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\left[\begin{array}{c} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{array}\right] \times 32$	$\left[\begin{array}{c} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{array}\right] \times 48$
Classification	1 × 1	7 × 7 global average pool			
Layer		1000D fully-connected, softmax			



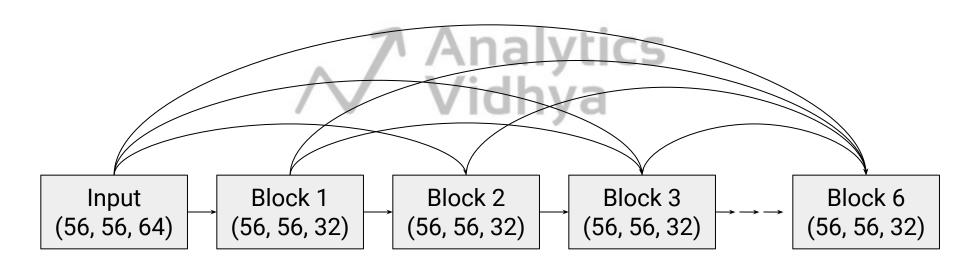
Layers	Output Size	DenseNet-121	DenseNet-169	DenseNet-201	DenseNet-264
Convolution	112 × 112	$7 \times 7$ conv, stride 2			
Pooling	56 × 56	$3 \times 3$ max pool, stride 2			
Dense Block (1)	56 × 56	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\left[\begin{array}{c} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{array}\right] \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$
Transition Layer	56 × 56		1 × 1	l conv	4
(1)	28 × 28		2 × 2 average	e pool, stride 2	
Dense Block (2)	28 × 28	$\left[\begin{array}{c} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{array}\right] \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\left[\begin{array}{c} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{array}\right] \times 12$	$\left[\begin{array}{c} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{array}\right] \times 12$
Transition Layer	28 × 28		1 × 1	l conv	
(2)	14 × 14		2 × 2 average	e pool, stride 2	
Dense Block (3)	14 × 14	$\left[\begin{array}{c} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{array}\right] \times 24$	$\left[\begin{array}{c} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{array}\right] \times 32$	$\left[\begin{array}{c} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{array}\right] \times 48$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 64$
Transition Layer	14 × 14	$1 \times 1 \text{ conv}$			
(3)	7 × 7		2 × 2 average	e pool, stride 2	
Dense Block (4)	7 × 7	$\left[\begin{array}{c} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{array}\right] \times 16$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\left[\begin{array}{c} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{array}\right] \times 32$	$\left[\begin{array}{c} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{array}\right] \times 48$
Classification	1 × 1	7 × 7 global average pool		100	
Layer			1000D fully-cor	nnected, softmax	





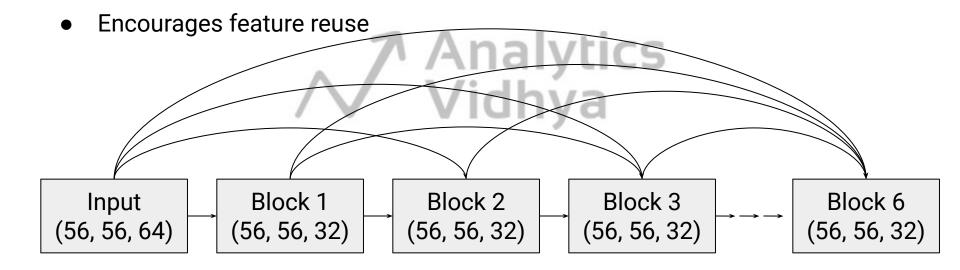


Resolves the issue of vanishing gradients





Resolves the issue of vanishing gradients





Resolves the issue of vanishing gradients

Encourages feature reuse

Analytics
Reduces number of parameters idhya







Model	Top-5 Error
DenseNet-121	Analytic <del>z.</del> 71%
	/idhya



Model	Top-5 Error
DenseNet-121	nalytic <del>7.</del> 71%
DenseNet-169	dhya 6.85%



Model	Top-5 Error
DenseNet-121	nalytic <del>7.</del> 71%
DenseNet-169	dhya 6.85%
DenseNet-201	6.34%



Model	Top-5 Error
DenseNet-121	nalytic <del>7.</del> 71%
DenseNet-169	dhya 6.85%
DenseNet-201	6.34%
DenseNet-264	6.12%





