Image Feature Extraction and Classification Using CNN Architectures

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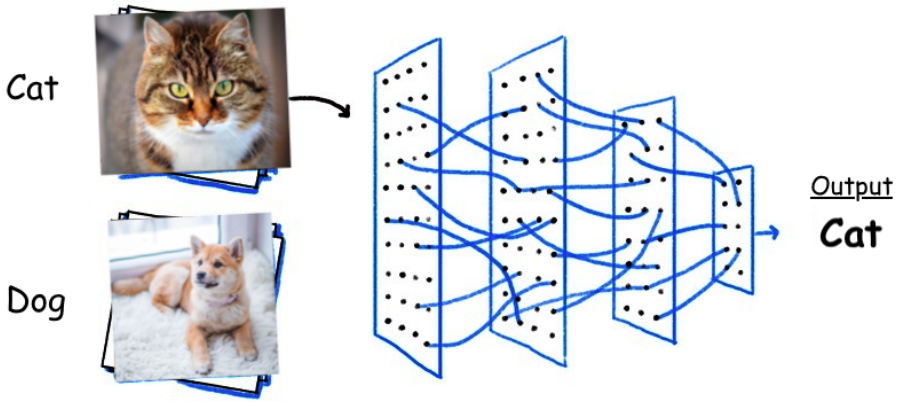
Learning Objective

- How features plays an important role in classification
- Implementation of different architectures for image classification

What is Image Classification

- Input is an image
- Output is a class label
- Example: cat, dog, car, person

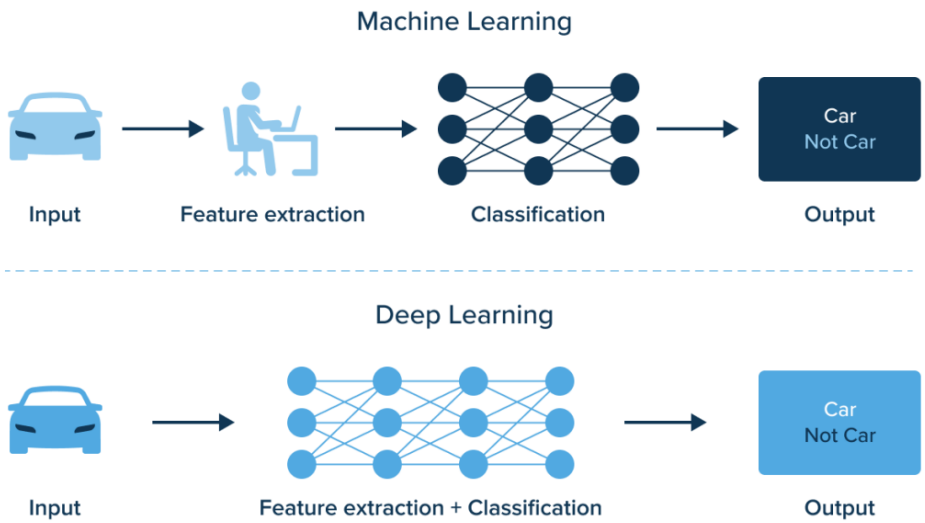
CNNs automatically learn useful patterns from images.



Why Do We Need CNNs

- Images have many pixels
- Manually designing features is difficult
- CNNs learn features directly from data

CNNs replace hand crafted features with learned features.



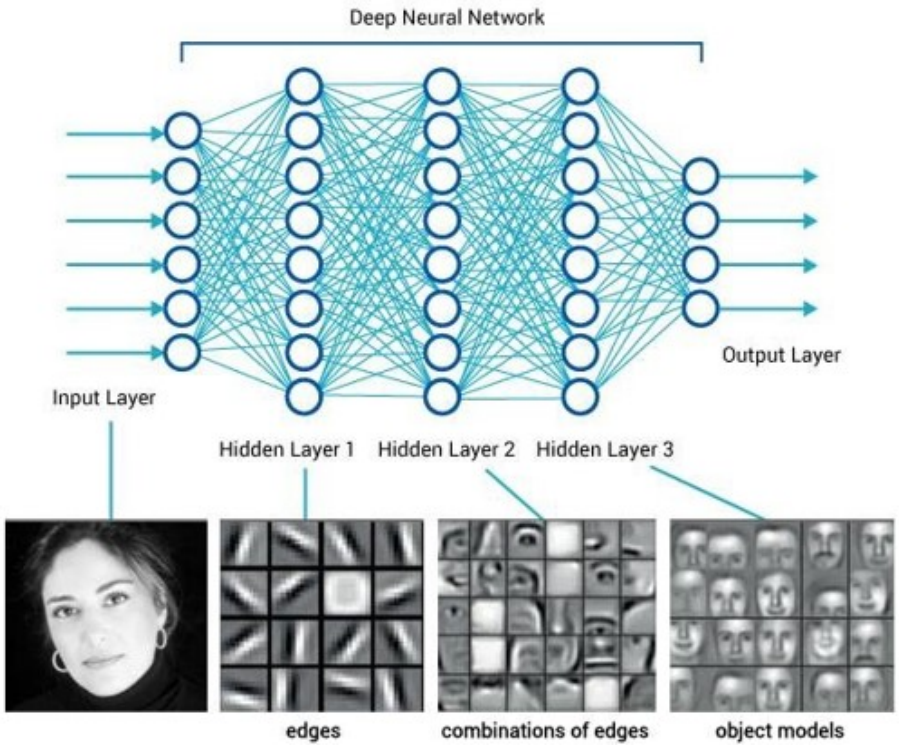
Two Main Parts of a CNN

1. **Feature Extraction**
   - Convolution layers
   - Pooling layers
2. **Classification**
   - Fully connected layers
   - Softmax output

How Feature Extraction Works

- First layers detect edges
- Middle layers detect shapes
- Deeper layers detect objects

Feature learning becomes more meaningful with depth.



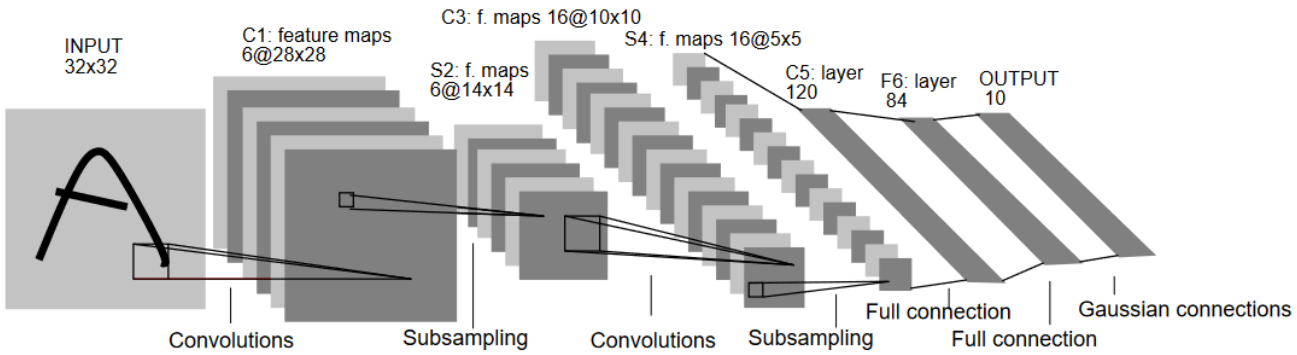
Why Count Parameters

- Parameters represent what the model learns
- More parameters means more memory usage
- More parameters increase training and inference time

Understanding parameter count helps choose the right model.

LeNet

- One of the first CNNs
- Few convolution layers
- Used for digit recognition



Simple model for simple images.

LeNet Parameters

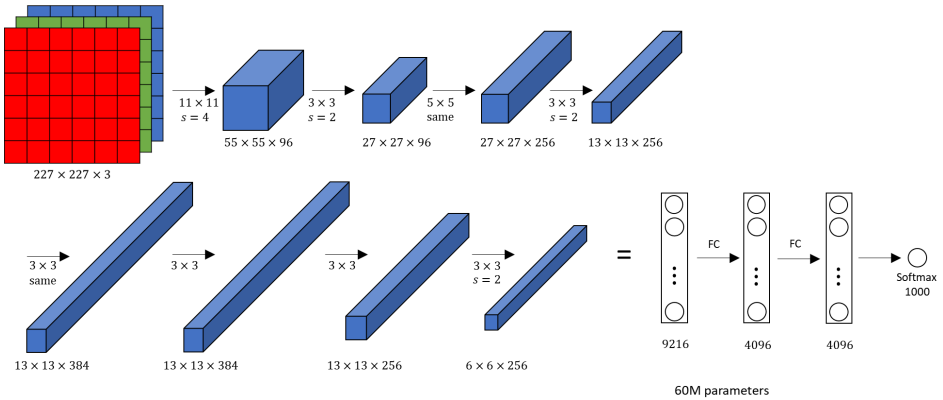
- Small filters
- Few channels
- Very low parameter count

Layer Name	Input W×H×D	Kernel W×H×D/S	Output W×H×D	Params	Mults
C1: conv2d	32×32×1	5×5×6	28×28×6	1×5×5×6+6 =156	28×28×1×5×5×6 =117,600
S2: pool/2	28×28×6	2×2/2	14×14×6	0	0
C3: conv2d	14×14×6	5×5×16	10×10×16	6×5×5×16+16 =2,416	10×10×6×5×5×16 =240,000
S4: pool/2	10×10×16	2×2/2	5×5×16	0	0
C5: conv2d	5×5×16	5×5×120	1×1×120	16×5×5×120+120 =48,120	1×1×16×5×5×120 =48,000
F6: conv2d	1×1×120	1×1×84	1×1×84	120×1×1×84+84 =10,164	120×84 =10,080
F7: conv2d	1×1×84	1×1×10	1×1×10	84×1×1×10+10 =850	84×40 =840
			Total	61,706	416,520

LeNet is lightweight and easy to train.

AlexNet

- Deeper than LeNet
- Works on larger images
- Uses ReLU and dropout



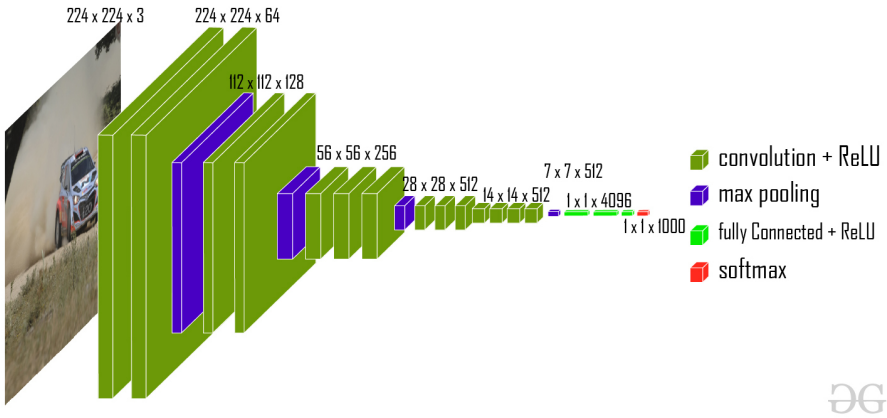
Showed that deep CNNs work well.

AlexNet Parameters

	Activation shape	Activation size	# parameters
Input image	227 x 227 x 3	154587	0
Conv 1	55 x 55 x 96 (f=11 s = 4 p = 0)	290400	34944
Pool 1	27 x 27 x 96 (f=3 s = 2)	69984	0
Conv 2	27 x 27 x 256 (f=5 s = 1 p = 2)	186624	614,656
Pool 2	13 x 13 x 256 (f=3 s = 2)	43264	0
Conv 3	13 x 13 x 384 (f=3 s = 1 p = 1)	64896	885,120
Conv 4	13 x 13 x 384 (f=3 s = 1 p = 1)	64896	1,327,488
Conv 5	13 x 13 x 256 (f=3 s = 1 p = 1)	43264	884,992
Pool 5	6 x 6 x 256 (f=3 s = 2)	9216	0
FC 3	4096 x 1	4096	37,748,737
FC 4	4096 x 1	4096	16,777,217
Softmax	1000 x 1	1000	4096001

VGGNet

- Many layers
- Uses only small 3×3 filters
- Easy to understand structure



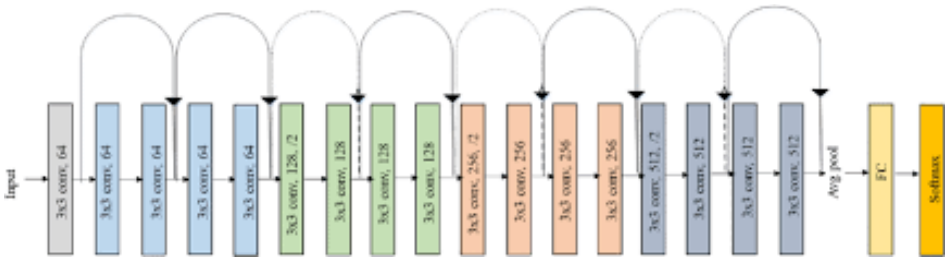
Deeper networks learn better features.

Problem with Very Deep Networks

- Training becomes difficult
- Gradients can vanish
- Accuracy may stop improving

ResNet

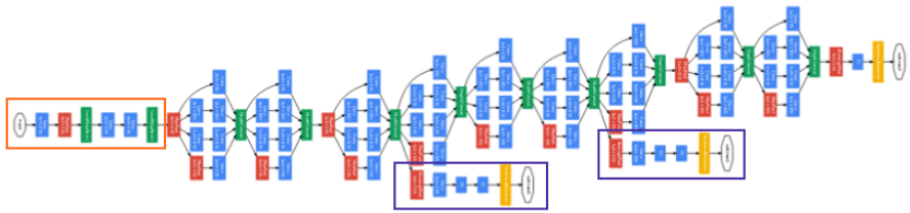
- Uses shortcut connections
- Skips some layers
- Makes training easier



Allows very deep CNNs.

InceptionNet

- Uses multiple filter sizes together
- Looks at image at different scales
- Efficient and accurate



GoogLeNet. The orange box is the **stem**, which has some preliminary convolutions. The purple boxes are **auxiliary classifiers**. The wide parts are the inception modules. (Source: Inception v1)

Combines multiple views of the image.