Image segmentation: U-Net

UNet is a convolutional neural network (CNN) architecture designed primarily for biomedical image segmentation, introduced in 2015. It follows a **U-shaped** structure with an encoder-decoder design.

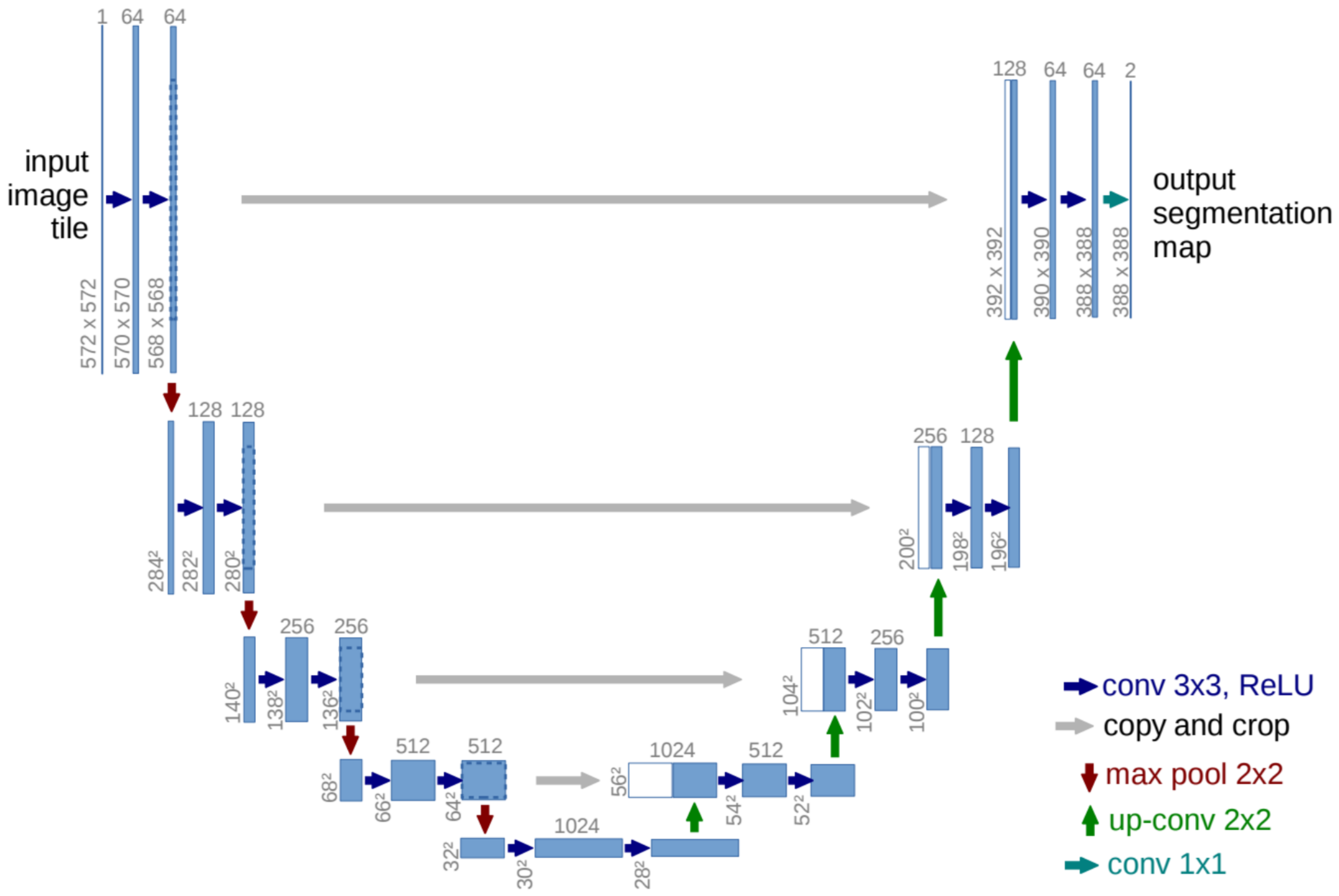
The encoder (**contracting path**) consists of convolutional and pooling layers that progressively extract spatial features and reduce the image size, similar to a traditional CNN.

The decoder (**expanding path**) uses upsampling and skip connections to restore spatial resolution while maintaining fine details, enabling precise segmentation.

Skip connections link corresponding layers from the encoder to the decoder, preserving spatial information and allowing the network to learn both **global and local** features.

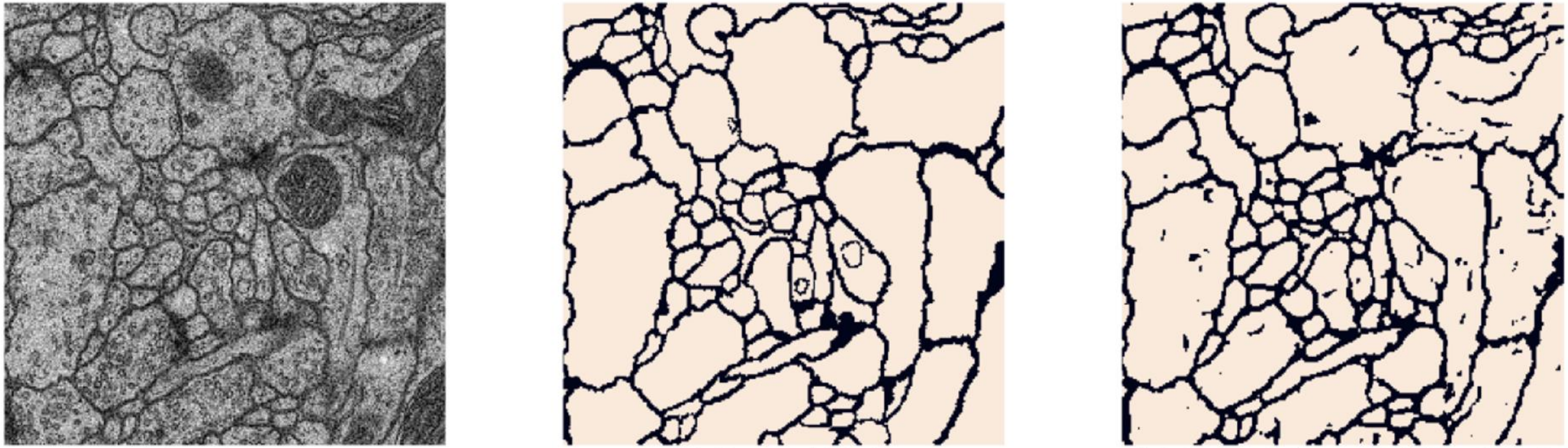
Olaf Ronneberger, Philipp Fischer, Thomas Brox, U-Net: Convolutional Networks for Biomedical Image Segmentation, MICCAI 2015

Image segmentation: U-Net



Olaf Ronneberger, Philipp Fischer, Thomas Brox, U-Net: Convolutional Networks for Biomedical Image Segmentation, MICCAI 2015

Image segmentation: U-Net

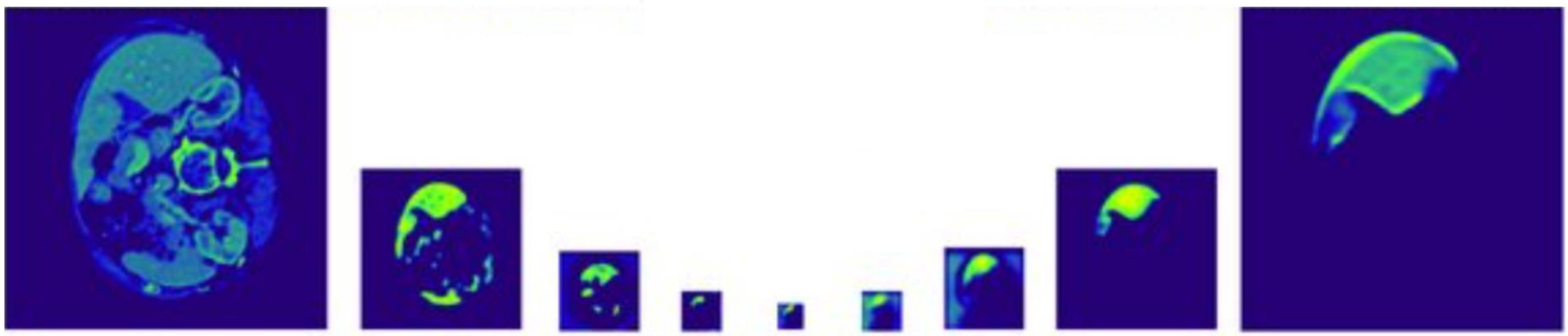


(a) Input Image (b) Ground Truth (c) Output from MultiResUNet

Olaf Ronneberger, Philipp Fischer, Thomas Brox, U-Net: Convolutional Networks for Biomedical Image Segmentation, MICCAI 2015

Image segmentation: U-Net

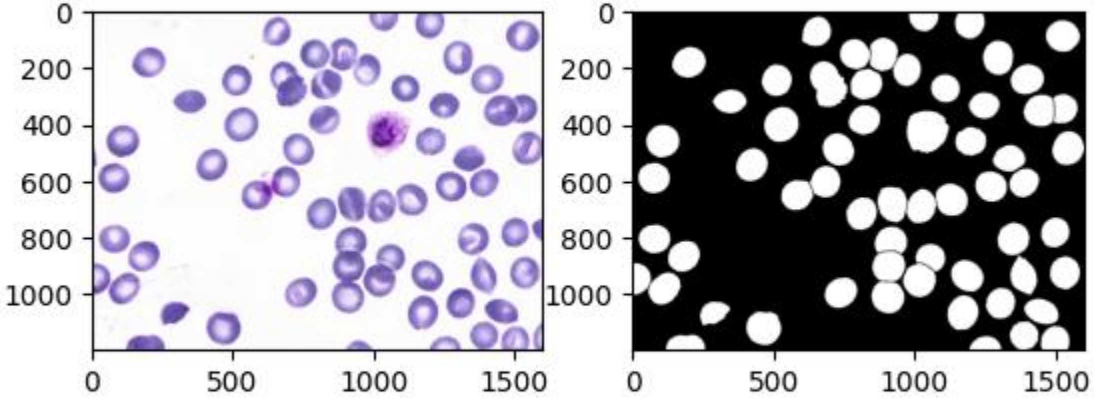
Apply U-Net to segment relevant regions in an image first, then use the segmented output to classify the image based on the presence, shape, or characteristics of the detected regions.



Olaf Ronneberger, Philipp Fischer, Thomas Brox, U-Net: Convolutional Networks for Biomedical Image Segmentation, MICCAI 2015

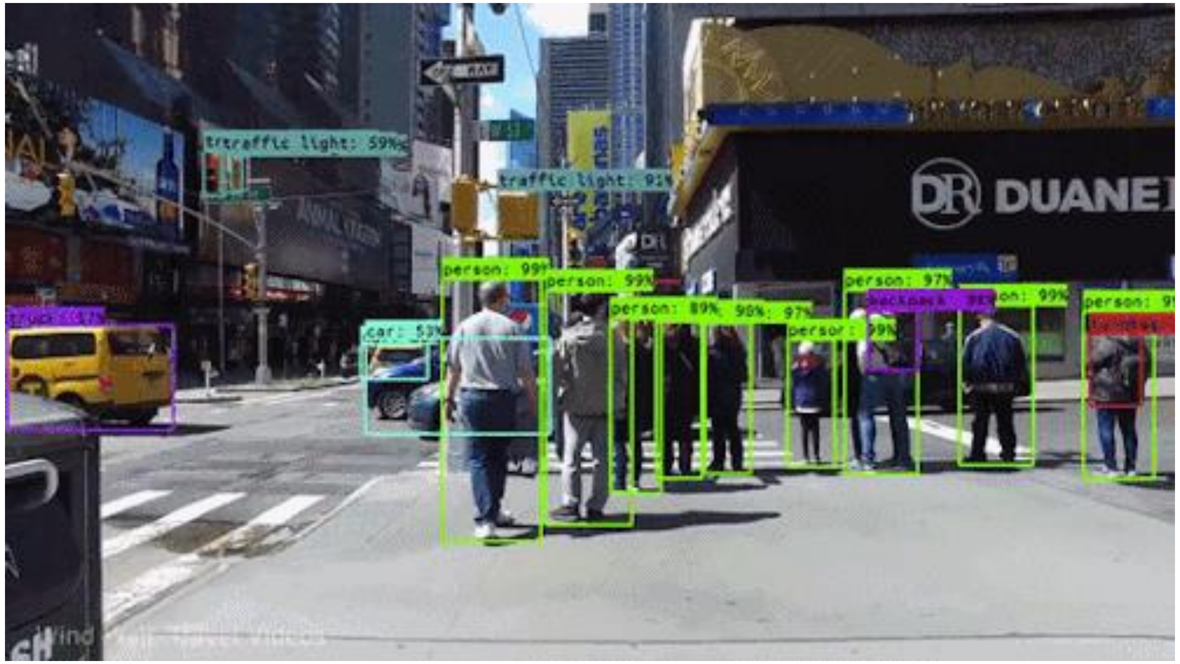
U-Net

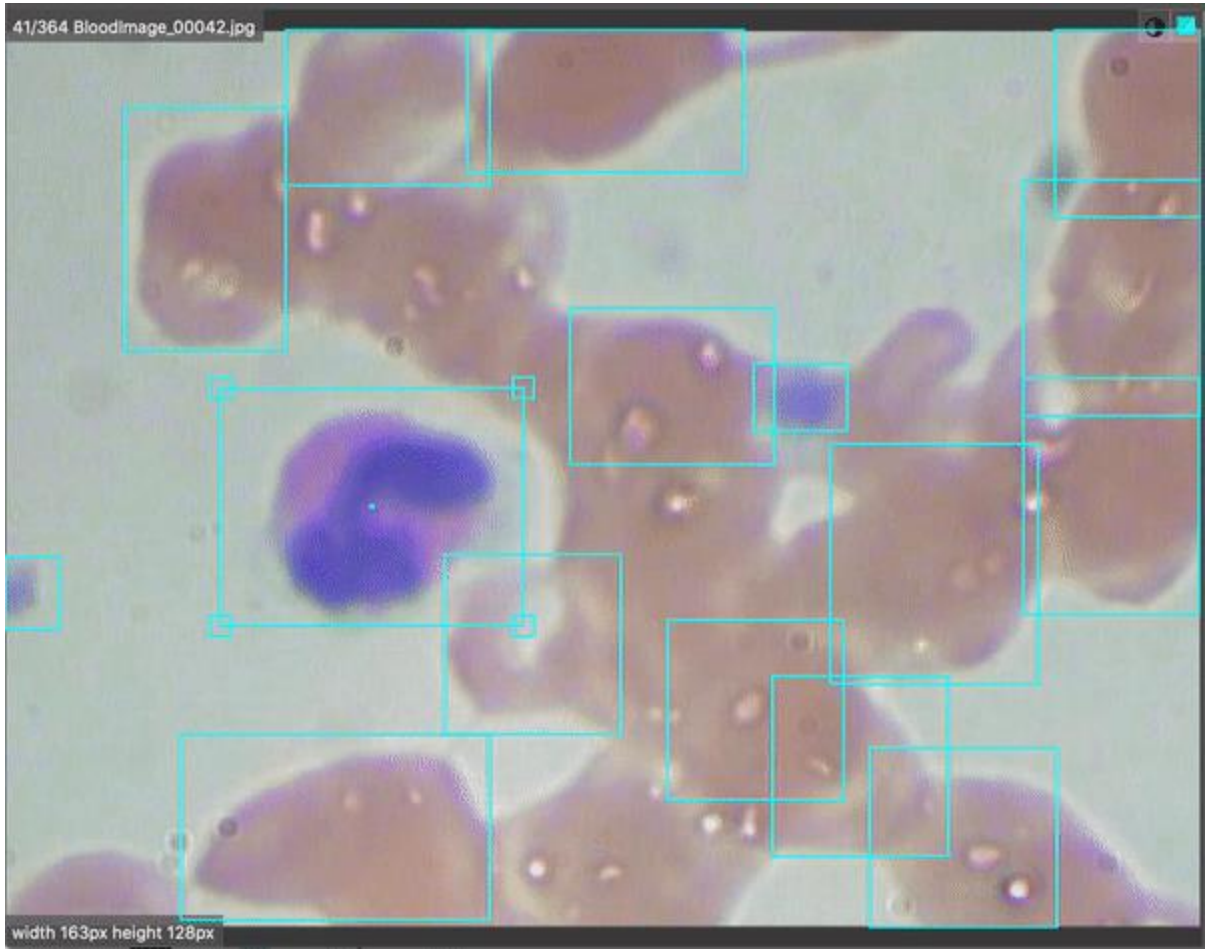
GitHub



unet-blood-cell-segmentation.ipynb

Object recognition: YOLO (You Only Look Once)





Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You Only Look Once: Unified, Real-Time Object Detection. CVPR

Object recognition: YOLO (You Only Look Once)

Grid-based detection: The image is divided into an **S×S grid**, where each grid cell is responsible for predicting objects whose centers fall within it.

Bounding box and class predictions: Each grid cell predicts **B bounding boxes** (with coordinates, width, height, and confidence scores) and C class probabilities, all in a single tensor.

Non-maximum suppression (NMS): To eliminate redundant detections, YOLO applies NMS, keeping only the highest-confidence bounding boxes while discarding overlapping ones.

Single-pass object detection: YOLO processes the entire image in one forward pass through a deep neural network, making it extremely fast.

Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You Only Look Once: Unified, Real-Time Object Detection. CVPR

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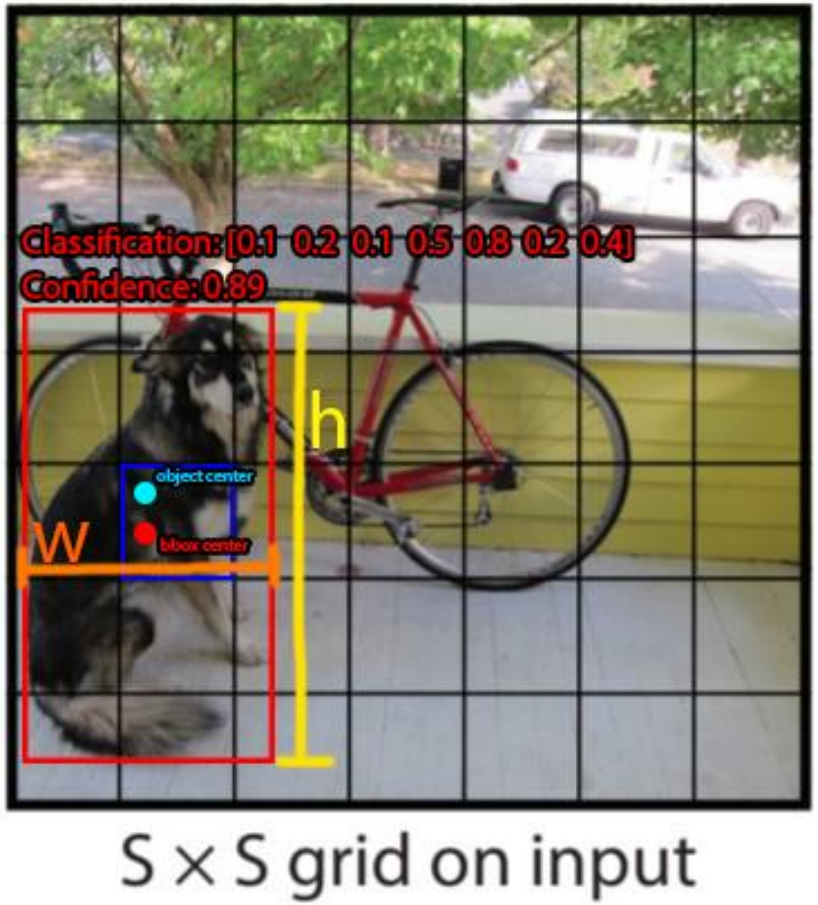

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Object recognition: YOLO (You Only Look Once)

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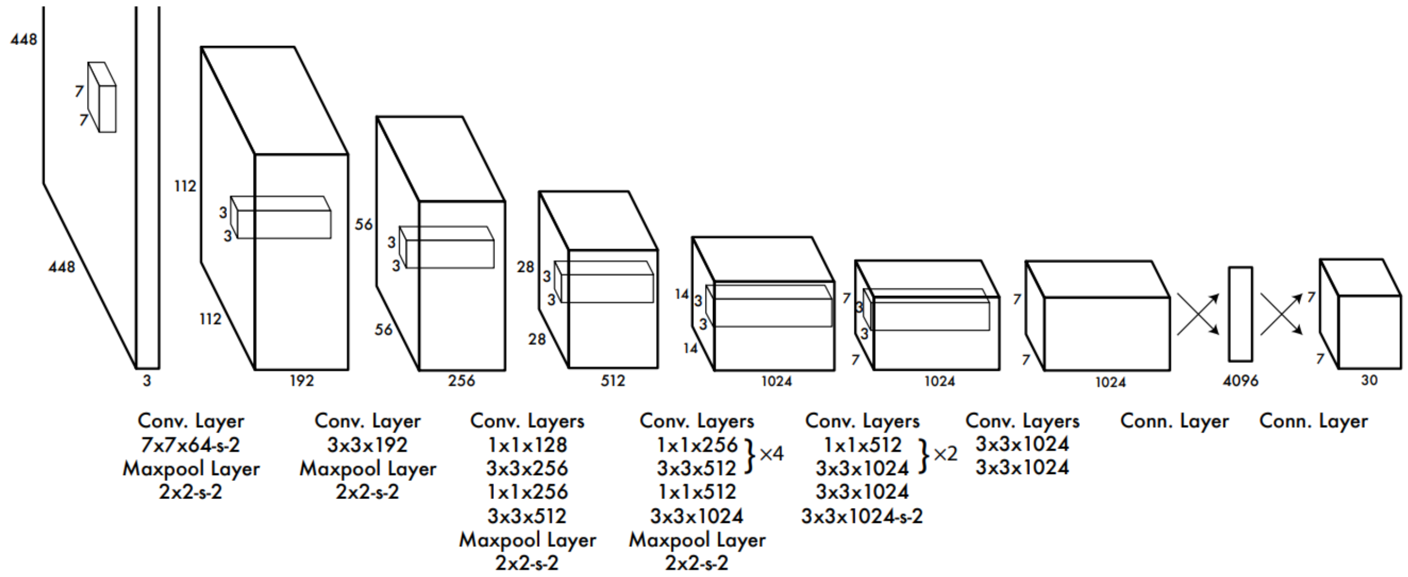
The final output of YOLO is a tensor of shape (S, S, B × (5 + C)), meaning:

- Each (i, j) position in this output tensor corresponds to the (i, j) grid cell in the original image.
- Each grid cell contains B bounding boxes, each predicting:
    - Object's center (x, y)
    - Size (w, h)
    - Confidence score
    - Class probabilities (C classes)



Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You Only Look Once: Unified, Real-Time Object Detection. CVPR

Common Objects in Context dataset (COCO)

COCO is a large-scale dataset for object detection, segmentation, and captioning that contains over 330,000 images with 1.5 million object instances across 80 categories.

It includes bounding boxes, object masks (segmentation), keypoints for human poses, and dense image captions, making it highly versatile for multiple computer vision tasks.

Serves as a benchmark dataset for state-of-the-art object detection and segmentation models, including YOLO and other deep learning architectures.

Lin, T.-Y. et al. (2014). Microsoft COCO: Common Objects in Context. ECCV 2014, pp. 740–755.

What computers see

206	205	247	245	244	253	247	245	136	151	255	255	255	255	255	255	234	207	231	255	254	254	255	255	254	255	252	255	255	254	255	247
244	161	137	244	254	255	254	255	118	103	209	228	155	153	236	193	74	52	68	173	255	254	254	255	255	255	254	255	254	253	244	184
192	154	75	200	249	255	255	255	110	98	84	61	35	44	89	53	44	45	43	54	140	213	253	255	255	255	255	245	187	186	176	223
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55	51	45	134	218	251	255	232	51	12	28	33	24	24	46	75	82	78	71	68	58	53	67	90	136	228	208	158	253	246	249	255
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32	38	52	54	159	250	126	57	129	138	138	140	151	156	166	168	171	178	180	187	186	185	185	183	180	102	136	242	255	255	254	254
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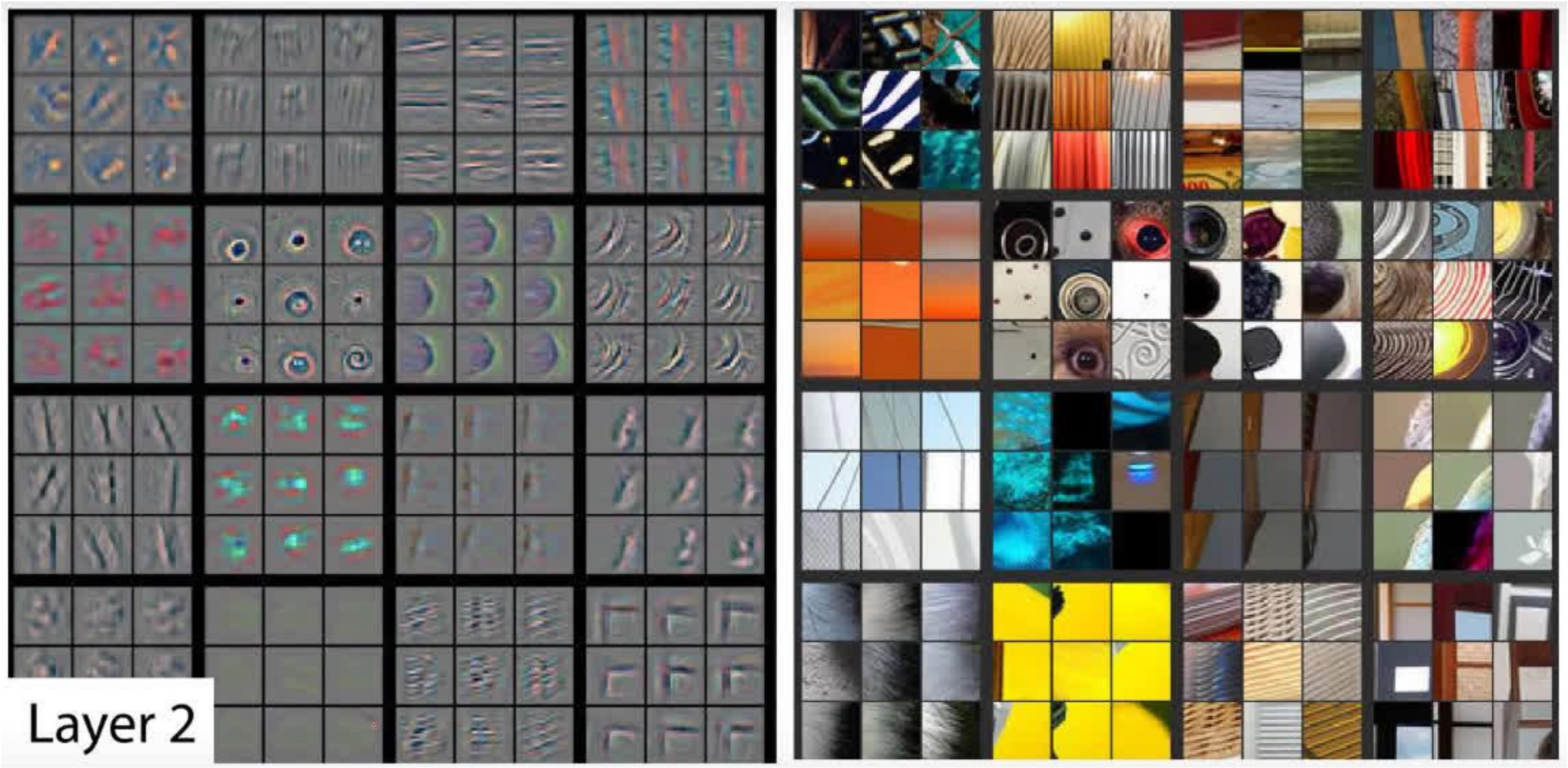
117	119	125	130	139	106	18	29	44	58	70	102	133	147	168	197	212	215	210	195	177	152	133	195	57	59	126	151	145	143	142	141
115	123	126	134	145	102	27	54	52	38	45	69	105	135	175	189	193	216	206	166	139	111	164	203	74	5	121	151	142	142	143	146
101	108	123	121	132	105	44	40	31	35	57	44	58	101	147	144	138	163	145	94	90	145	196	187	84	48	165	160	142	144	142	145
98	97	97	98	104	76	34	33	30	48	41	49	51	58	74	53	55	66	63	89	150	188	209	156	62	108	140	149	125	133	131	131
102	102	97	88	73	35	30	23	42	50	65	41	90	60	59	51	57	82	123	157	187	205	169	62	98	151	106	101	154	135	130	129

What computers see

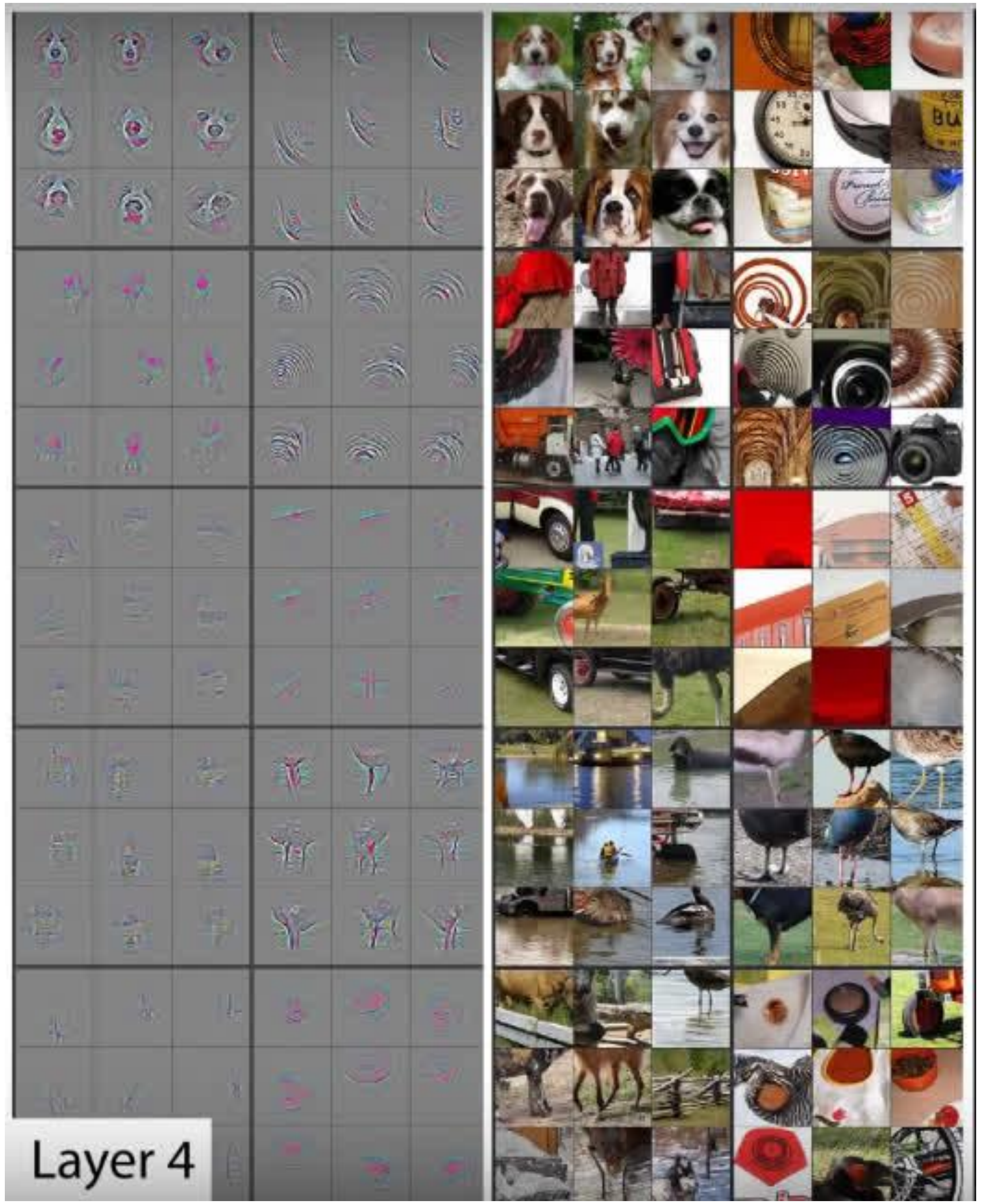
On the left, each square is a different feature map (convolutional filter) with the activations shown for the corresponding images on the right (these images are selected such that they maximize the activation of the filter.



Zeiler, M. D., & Fergus, R. (2014, September). Visualizing and understanding convolutional networks. In European conference on computer vision (pp. 818-833)

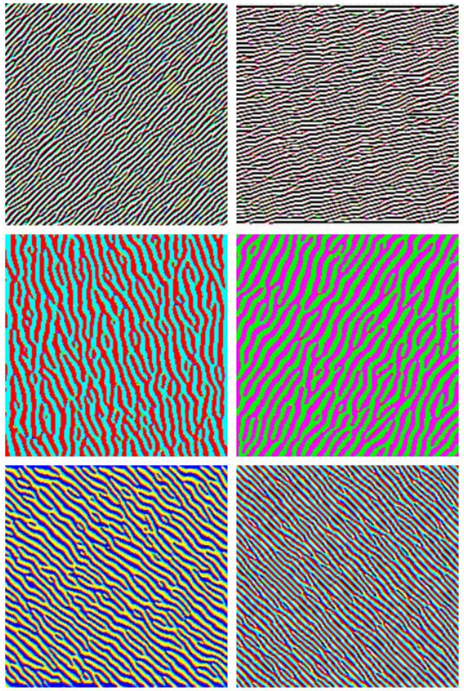
What computers see

The patterns that the filters detect become more complex as we go deeper into the network.

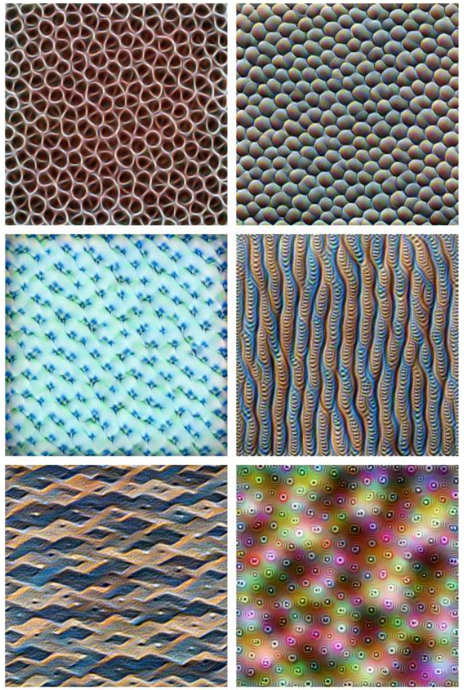


Zeiler, M. D., & Fergus, R. (2014, September). Visualizing and understanding convolutional networks. In European conference on computer vision (pp. 818-833)

What computers see

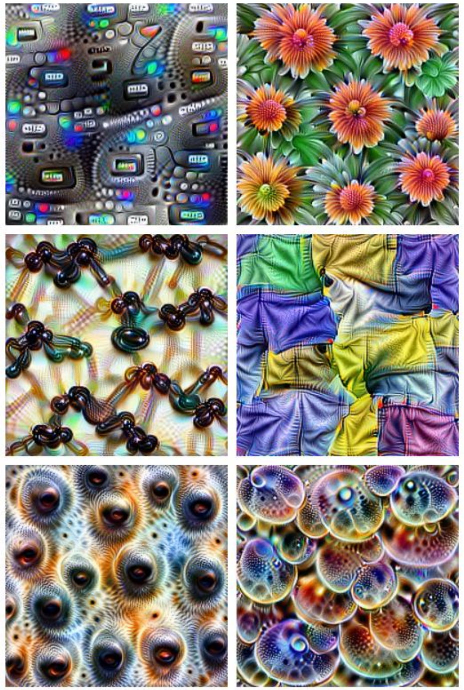


Edges (layer conv2d0)



Textures (layer mixed3a)

Patterns (layer mixed4a)

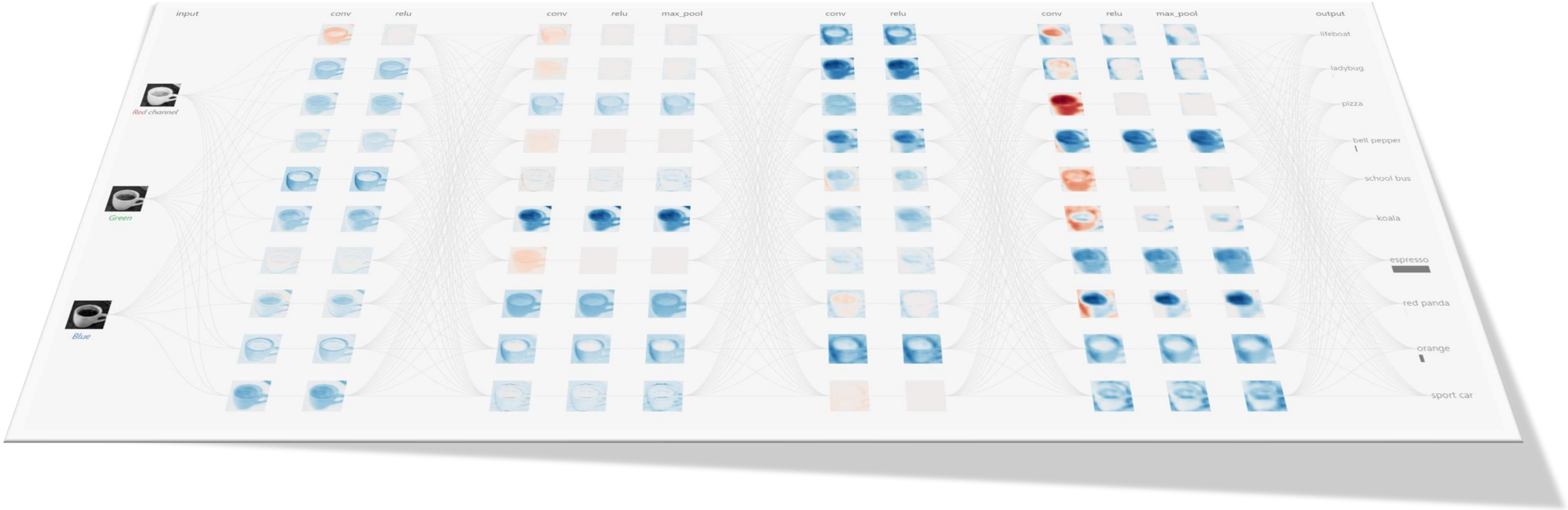


Parts (layers mixed4b & mixed4c)

Objects (layers mixed4d & mixed4e)

https://distill.pub/2017/feature-visualization/

What computers see



https://poloclub.github.io/cnn-explainer/

Activation maximization

Activation Maximization is a technique used to visualize what a CNN has learned by generating an input that **maximally activates** a specific neuron or filter.

It involves optimizing an input image using **gradient ascent** to enhance the activation of a target neuron, layer, or class score while applying regularization techniques (e.g., total variation loss, L2 norm) to ensure interpretability.

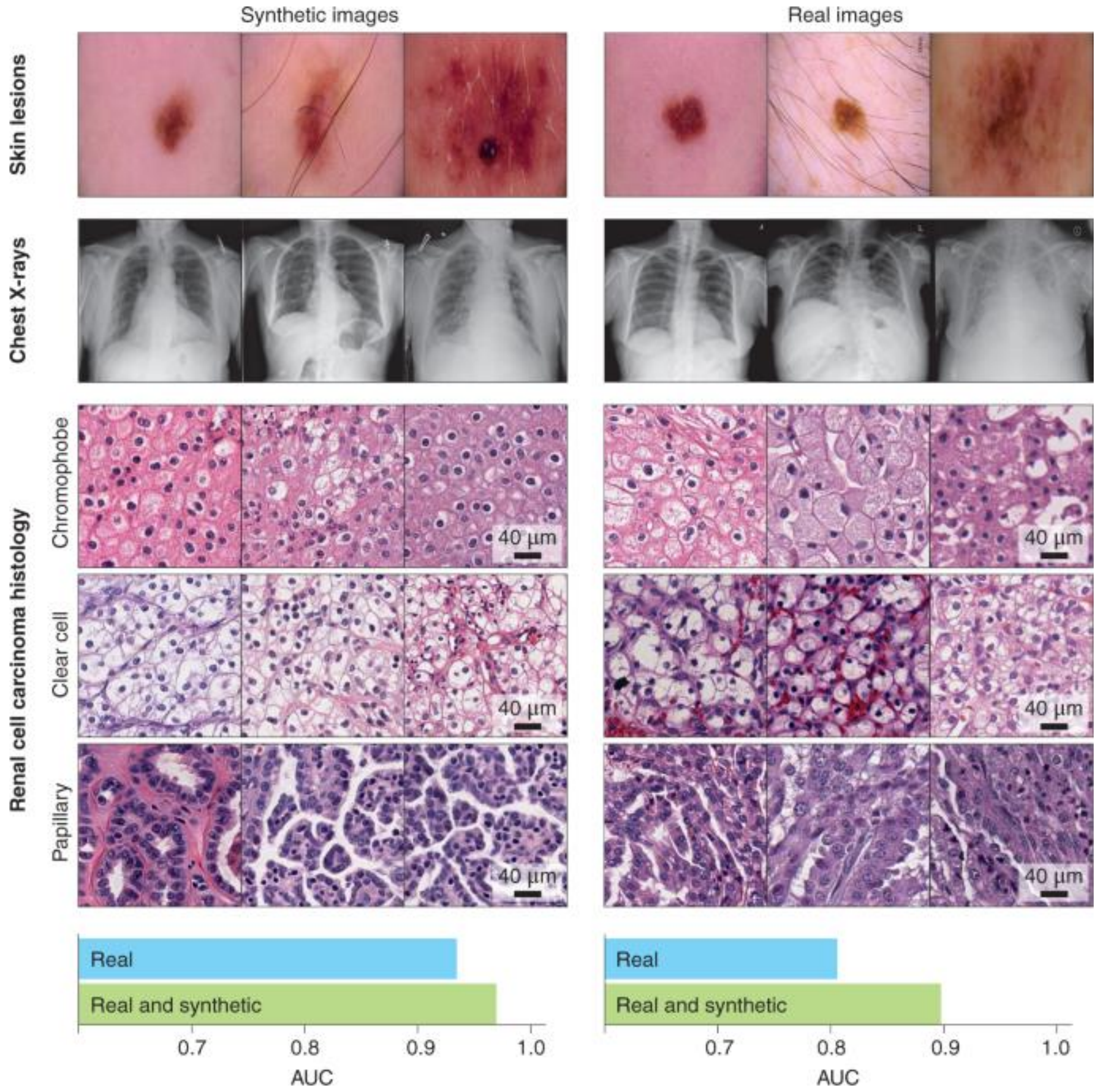
Activation maximization

Activation maximization

X-rays, MRIs, pathology slides.

By generating **synthetic** images that **maximally activate certain neurons**, we can visualize the features a model uses to detect tumors, fractures, or diseased tissues.

Generating synthetic images offers an ethical alternative to using **sensitive patient data**, helping with education and training without compromising patient privacy



Activation maximization

DNA/RNA sequences or protein structures: Generating **synthetic sequences** that maximize disease-associated neuron activations.

Optimizing molecular structures: **Chemical structures or molecular fingerprints**, e.g. revealing which molecular features trigger activation in neurons predicting drug activity.

Transfer learning

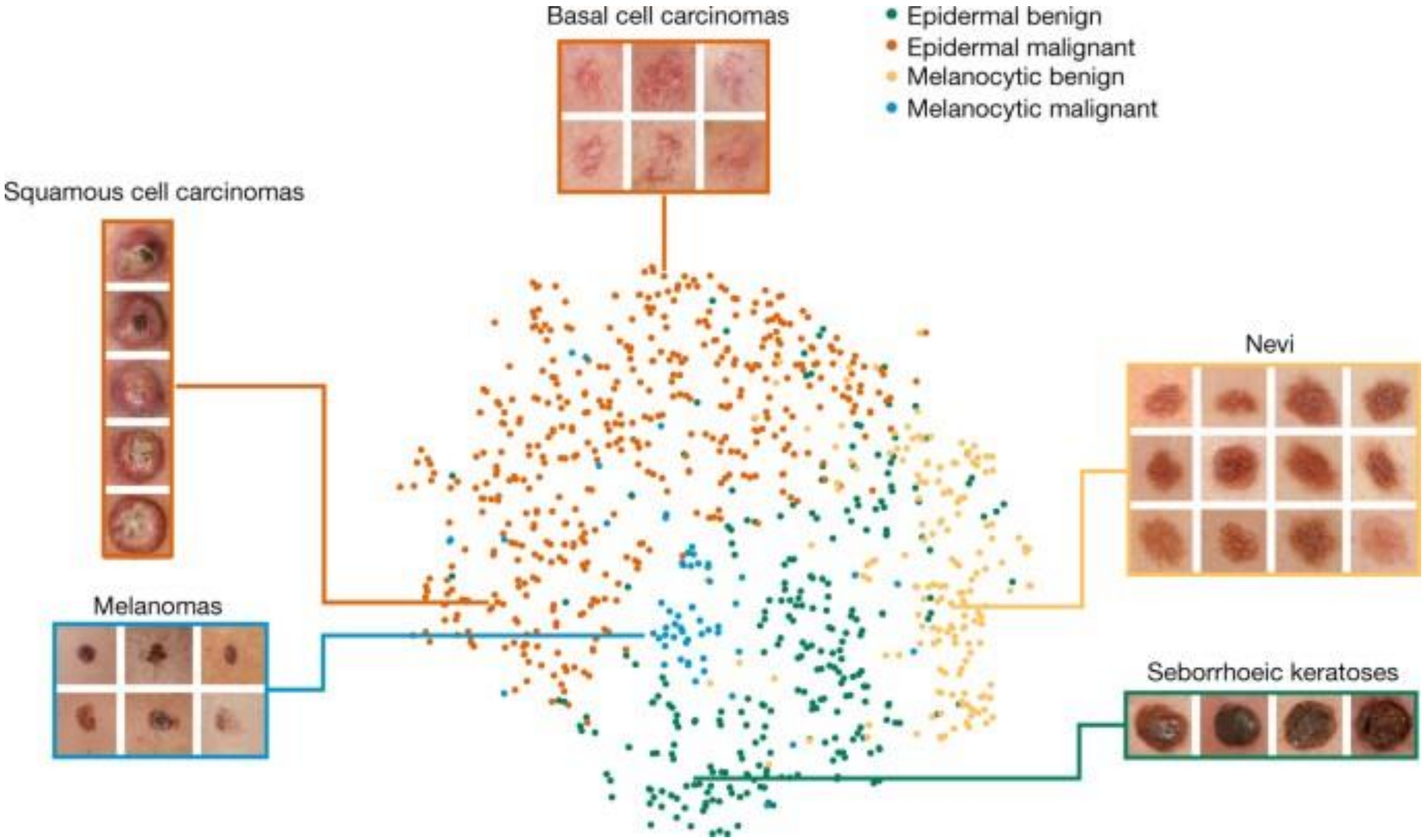
Transfer learning is a machine learning technique where a pre-trained model, trained on a large dataset (e.g., ImageNet for vision or BERT for NLP), is adapted to a new but related task with limited data..

It significantly **reduces training time** and computational costs by leveraging previously learned features instead of training a model from scratch.

Common approaches include **fine-tuning** (modifying and retraining some layers) and **feature extraction** (using pre-trained layers as fixed feature detectors).

Pre-training positions a deep neural network closer to the optimal solution in the vast, high-dimensional model parameter space, enabling faster convergence and better performance compared to starting from random initialization.

Transfer learning



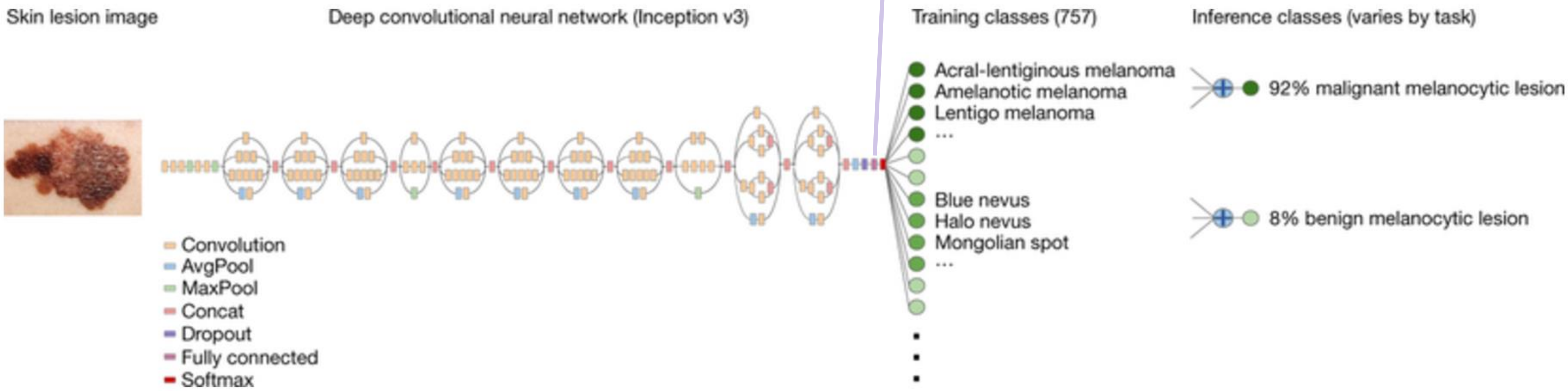
Thrun et al., Dermatologist-level classification of skin cancer with deep neural networks, Nature (2017)

Transfer learning

A **pre-trained** (on ImageNet) Inception v3 CNN was downloaded from GitHub.

The fully connected feed forward neural network module was replaced.

The network was then **fine-tuned** on the available lesion data. This means that the remainder of the modelparameters were used as the network's initialization.



Thrun et al., Dermatologist-level classification of skin cancer with deep neural networks, Nature (2017)