CLASSIFICATION HISTORY

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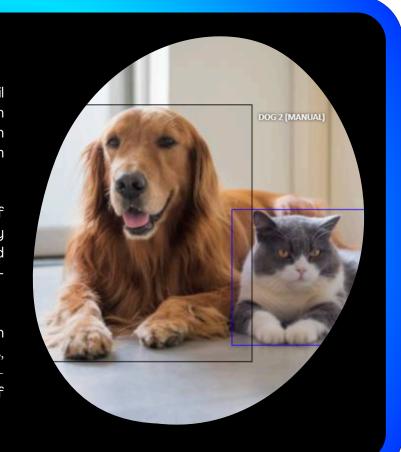
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INTRODUCTION

Classification problems are everywhere—in e-mail spam filtering, medical diagnosis, image recognition and beyond. By harnessing the power of modern computers, we can train algorithms to learn from data and automate these tasks at scale.

This visualization traces the evolution of classification models over time, highlighting key breakthroughs in model architecture and computational capacity that have driven ever-improving performance.
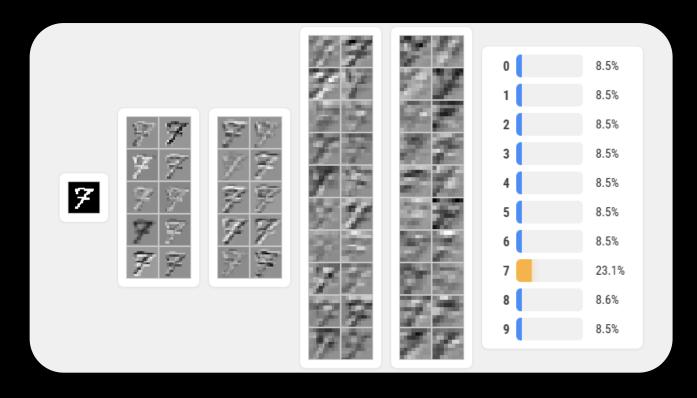
For example, your smartphone's photo gallery can automatically sort pictures—grouping landscapes, portraits, and even distinguishing cats from dogs—so you can easily find that adorable snapshot of your pet.
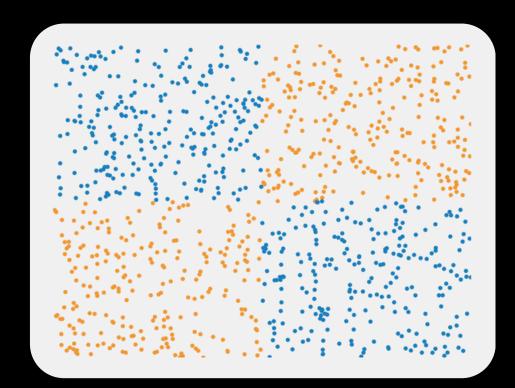
WHAT'S CLASSIFICATION ?

Classification is nothing more than giving a set of labels (or classes) and a set of data, assigning a label (or more than one depending on the case) to each piece of data. In a more direct way, classification is the process of identifying which category a new piece of data belongs to, based on a set of already labeled data.

With the emergence of computers to assist in calculations and other complex tasks, the question arose: "Why not teach the computer to classify objects too?".

LIVE CNN

This necessity paved the way for the development of Convolutional Neural Networks (CNNs), a revolutionary architecture inspired by the human visual cortex. Unlike MLPs, CNNs utilize convolutional layers to automatically and adaptively learn spatial hierarchies of features, from simple edges and corners to more complex motifs. By incorporating concepts like parameter sharing and pooling layers, CNNs could efficiently process raw pixel data, capture the spatial dependencies, and achieve a high degree of invariance to transformations like translation and scaling.

To show how these CNNs work, we built an interactive CNN where the user can draw a number from MNIST and see under the hood of the CNN. This is the highlight of the storytelling, allowing the user to interact and engage with the project.

0	8.5%
1	8.5%
2	8.5%
3	8.5%
4	8.5%
5	8.5%
6	8.5%
7	23.1%
8	8.6%
9	8.5%

HISTORY

In 1958, Frank Rosenblatt introduced the Perceptron—a single-layer, linear classifier that learns by tuning its input weights to find a hyperplane separating two classes.

A decade later, Marvin Minsky and Seymour Papert demonstrated that this model cannot solve the XOR problem—a simple task where the output is 1 if two binary inputs differ, and 0 if they're the same. No straight line can split the XOR pattern into its two classes.

In the chart above, you'll see exactly this limitation: blue and orange points arranged so that no single hyperplane can separate them, highlighting why non-linear, multi-layer networks were needed to advance classification.

In 1986, David Rumelhart, Geoffrey Hinton and Ronald Williams showed that adding hidden layers and using the backpropagation algorithm allows networks to learn non-linear decision boundaries—overcoming the XOR barrier and kick-starting the era of modern neural networks.

CONCLUSION

While CNNs unlocked unprecedented accuracy in image classification, other algorithmic families also made their mark. Kernel-based support vector machines can carve complex decision boundaries in high-dimensional spaces, and ensemble methods like Random Forests and gradient-boosted trees deliver robust performance by combining simpler predictors.

The deep-learning community never rested on vanilla CNNs alone. Residual Networks (ResNets, 2015) overcame vanishing gradients to train extremely deep models; DenseNets (2017) introduced dense connectivity for improved feature reuse; and EfficientNets (2019) applied compound scaling to balance network depth, width, and resolution—achieving top performance with fewer parameters.

Today's frontier is driven by attention. Vision Transformers (ViT, 2020) brought self-attention to image patches, learning global context without convolution, and hierarchical variants like Swin Transformers fuse convolutional inductive biases with multi-scale attention. As models grow in power—and computational cost—future progress will hinge on balancing accuracy, efficiency, and sustainability, paving the way for ever-more capable classification systems.

Notable AI Models: Training Compute vs Publication Date

Training Compute (FLOP) [log scale] vs Publication Date