

Lecture #02. Convolutional Neural Networks

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## **Agenda**

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CNNs: the Current State and Prospects

Conclusion

1 Outcomes

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### **Section 1. Outcomes**



### **Outcomes**

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This week's lecture and practice on CNNs is designed to provide a deep understanding of the theoretical concepts and practical skills necessary for working with CNN-based architectures. By the end of this lecture, students will be able to:

- Understand core concepts: convolutions, filters, feature maps, padding, pooling, and key CNN architectures (e.g., ResNet, DenseNet, ConvNeXt).
- 2 Apply transfer learning and fine-tuning to adapt pre-trained models for new tasks using tools like PyTorch.
- 3 Implement CNNs on datasets like MNIST and CIFAR-10, bridging the gap from educational tasks to real-world applications.

Key Takeaway: Transfer learning accelerates solving practical problems by leveraging pre-trained models.

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# Section 2. Key Ideas in CNNs



### Physiology of cats

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Figure: Responses of the cat's visual cortex cell.

### Implementation in math.

The horizontal derivative kernel approximates  $\frac{\partial I}{\partial x}$  using **finite differences**. For images, this translates to computing intensity changes along the x-axis. The Sobel kernel for horizontal derivative is:

$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

This kernel computes:

$$\frac{\partial I}{\partial x} \approx (I(x+1,y) - I(x-1,y))$$

and incorporates smoothing to reduce noise. It detects horizontal edges by highlighting intensity changes from left to right.



# Hands-on coding: Kernels [CV-2025]

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#	Filter	Description
1	Median Filtering	Replaces each pixel with the median value of its neighborhood.
2	Gaussian Blur	A Gaussian kernel. Reduces noise but blurs edges.
3	Bilateral Filtering	Smooths the image while preserving edges by considering both spatial and intensity differences.
4	Non-Local Means Denoising	Removes noise by averaging similar patches across the image. Computationally intensive.
5	Histogram Equaliza- tion	Redistributes pixel intensities to improve contrast. Simple and effective for enhancing details.
6	Edge Detection (Canny)	Detects edges using gradient-based methods and hysteresis thresholding. Preserves strong edges.
7	Thresholding	Converts a grayscale image to binary based on a threshold value. Simple pixel-wise operation.
8	Morphological Operations (Closing)	Closes small defects in binary images using a structuring element.
9	Inpainting	Fills missing or corrupted regions in the image using surrounding information. Solves partial differential equations.



## Padding, Pooling, and Striding

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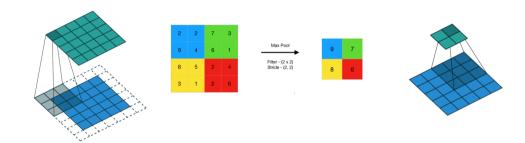


Figure: Padding (left), Pooling (middle), and Striding (right). CNNs by Neurohive.



## 2D Convolution Applied to an Image

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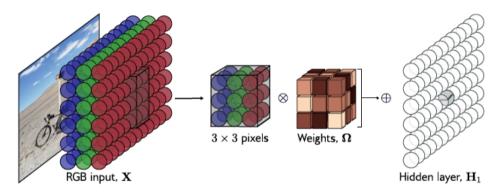
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### Result of a convolution

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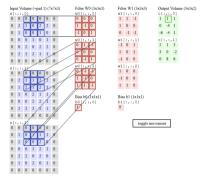
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### The result of convolving an image

of size [q, q] with a kernel of size [k, k], with padding [p, p] and stride [s, s], is a matrix of size [r, r]:

$$r = \frac{q - k + 2p}{s} + 1 = \frac{5 - 3 + 2}{2} + 1 = 3.$$

Figure: CS231n: CNNs.



## Hands-on the book by Howard and Gugger [2020]

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CNN utilizes the features of the visual cortex, where simple cells are activated by simple features (such as lines), and complex cells by combinations of activations of simple cells. The CNN is associated with the mathematical operation of convolution for reducing matrix sizes.

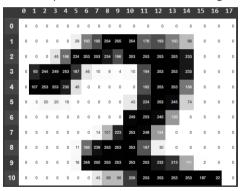


Figure: Check the code: 13 convolutions.ipynb, and 14 resnet.ipynb



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# Section 3. CNNs: the Current State and Prospects



## **Paper Reading**

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The following review papers on CNNs [Kiranyaz et al., 2021; Li et al., 2021] are the most cited in 2025:

- 1 1D Convolutional Neural Networks and Applications A Survey
- 2 A Survey of Convolutional Neural Networks: Analysis, Applications, and Prospects



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### **Section 4. Conclusion**



### **Conclusion**

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### **Summary:**

- Convolutions reduce parameters and improve efficiency by enforcing structured connectivity, enabling deeper models with less overfitting.
- Thoughtful architecture design (e.g., convolutions) outperforms theoretical but impractical fully connected networks in real-world applications.
- Scheduling the learning rate, batch normalization, and activation analysis are key tools for stabilizing training and monitoring progress, paving the way for advanced architectures like residual networks.



## **Bibliography**

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