

RAG Ingestion Verification Report

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Content Units

Unit 1 [image / vision]

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Unit 2 [image / vision]

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Unit 3 [image / vision]

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Unit 4 [image / vision]

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Unit 5 [text / ocr]

Unit ID: unit_824900ecf0f3497bb076bfd0f99ce3dd

Page: 1

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Page 1 of 22 1. INTRODUCTION TO CNN Convolutional Neural Networks (CNNs) are a special type of neural network designed to work well with image and spatial data (data arranged in a grid, like 2D images or even 1D time series). Instead of connecting every input pixel to every neuron (like a fully connected ANN), CNNs use small filters (kernels) that scan across the image to detect patterns. This approach allows the network to automatically learn useful visual features:

- o Early layers > detect edges and simple shapes.
- o Middle layers > detect textures or parts of objects.
- o Deeper layers > detect whole objects or complex patterns.

CNNs are parameter-efficient compared

to ANN: the same small filter is reused across the whole image (called weight sharing). This makes them faster to train and better at understanding images than a standard fully connected network.

1.1 Summary CNNs are neural networks specialized for grid-like data (like images) that learn visual features automatically and are far more efficient than fully connected ANNs. 1.2 Problem with ANN on images An image of size 64x64x3 (RGB) has 12,288 pixels. A single fully connected layer with just 100 neurons would need $12,288 \times 100 = 1.2\text{M}$ weights > huge, slow, prone to overfitting. CNN fixes this by using small filters that are reused across the image instead of learning a separate weight per pixel. 1.3 Why CNN (Convolutional Neural Networks) Uses small filters/kernels (e.g., 3x3, 5x5) that slide over the image. The same small set of weights is reused across the entire image (weight sharing). Learns local spatial patterns first (edges > shapes > objects). Far fewer parameters, trains faster, generalizes better.

Unit 6 [table | ocr]

Unit ID: unit_cfb2115ad70c407586c38d7b6f3e7ccc

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s)	that	scan	across	the	image	to	detect	patterns.	This	approach	allows	the	network	to	automatically	I
	pixel.															

Unit 7 [text | ocr]

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Page 2 of 22 2. HOW CNN WORKS — VISUAL INTUITION Think of an image as a grid of numbers (pixel values). A filter/kernel is a small grid of weights (e.g., 3x3) that slides (convolves) across the image: Input Image fe.g., 6x6) Ge & ae te HOS Or we @orRPNH® © PN HF @ @ He Ho OH fai camel} mah a Goma} mak opm} 3x3 Filter e = The filter slides over the image, multiplying and summing values > creates a feature map. e One filter may detect horizontal edges, another vertical edges, etc. e Stacking many filters helps the network learn different features automatically. 2.1 CNN Feature Learning Hierarchy e _ Layer 1: Learns edges (horizontal, vertical, diagonal). e Layer 2: Learns textures, corners. e —_ Layer 3+: Learns shapes and objects (faces, wheels, etc.). 2.2 One-liner for interviews: “CNNs use small filters that slide over an image to detect patterns. Early layers find simple edges; deeper layers combine them into complex shapes and objects — all with far fewer parameters than a fully connected ANN.” 2.3 ANN v CNN ANN CNN Fully connected — huge number of weights Convolution filters + very few weights Ignores spatial info Exploits local spatial structure Easily overfits on images Generalizes well 2.4 One-liner for Interviews “ANNs treat every pixel independently and explode in parameter count, while CNNs share small filters across the image, preserving spatial structure and using far fewer weights.”

Unit 8 [table | ocr]

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tes	a	feature	map.	e	One	filter	may	detect	horizontal	edges,	another	vertical
onal).	e	Layer	2:	Learns	textures,	corners.	e	—_	Layer	3+:	Learns	shapes
	detect	patterns.	Early	layers	find	simple	edges;	deeper	layers	combine	them	into
volution	filters	+	very	few	weights	Ignores	spatial	info	Exploits	local	spatial	structure
nt,	while	CNNs	share	small	filters	across	the	image,	preserving	spatial	structure	and

Content Hash: e78ede2c18f51a944d29eb7454145487e36a0d96a148c07f0b1535bafbc78f39

Page 7 of 22 Step 2 — Move 1 step right Next 3x3 patch: $\begin{bmatrix} 2 & 3 & 0 \\ 1 & 2 & 3 \\ 2 & 1 & 0 \end{bmatrix}$ Multiply with filter F: $(2*1) + (3*0) + (0*-1) + (1*1) + (2*0) + (3*-1) + (2*1) + (1*0) + (0*-1) = (2+0+0) + (1+0-3) + (2+0+0) = 2$ So, Output $[0,1] = 2$. You repeat this sliding process until the filter has scanned the whole 5x5 image. Since we used: $e = \text{Input} = 5 \times 5$ $e = \text{Filter} = 3 \times 3$ $e \text{ } \S = 6 @ \text{Stride} = 1$ $e = \text{Padding} = \text{Valid (no padding)}$ «© The Output feature map size = 3×3 . @ What do negative / zero / positive numbers in the feature map mean? When a filter slides over the image: e Each output number is the dot product (multiplication + sum) between the filter and the small patch of the image. e It's basically a score for "how well this patch matches the pattern" the filter has learned. Positive (large) / Patch matches the filter's pattern strongly. Patch doesn't match the pattern much. Patch matches the opposite of the filter's pattern. © Example: e If the filter learned to detect a vertical edge (bright on left, dark on right): o Positive > strong vertical edge found. o Zero > no vertical edge. o Negative > opposite edge (dark left, bright right). © Putting it together e You choose how many filters and their size (e.g., 32 filters of size 3×3). e The network learns what each filter detects during training (no need to hand-design).

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age:	e	Each	output	number	is	the	dot	product	(multiplication	+	sum)	between
tical	edge	found.	o	Zero	>	no	vertical	edge.	o	Negative	>	opposite
e	network	learns	what	each	filter	detects	during	training	(no	need	to	hand-design).