CNN Architecture, OpenCV & Data Augmentation

Course:
Deep Learning with Tensorflow & Kersa 2

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Current Section

Why Do We Need Convolution in Neural Networks?

Imagine trying to classify a 100x100 image with a fully connected ANN.

- **Each pixel** is treated as an independent feature.
- This results in $100 \times 100 = 10{,}000$ input features – very sparse, non-spatially aware.

Scalability Warning

Fully connected layers grow *quadratically* with input size – making them unsuitable for large images.

Problem: How do we efficiently detect local patterns (edges, textures, etc.) while preserving spatial structure?
Solution: Convolutional layers, which use local filters (kernels) and shared weights to learn spatial features.

$$Y(i,j) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} X(i+m, j+n) \cdot K(m,n)$$

A convolution applies a small kernel (filter) to different regions of the image, performing dot products to extract features.

Structure of a Convolutional Layer

Key Parameters:

- **Kernel Size (F)**: Size of the filter, e.g. 3×3, 5×5.
- **Stride (S)**: Number of pixels the filter moves each step.
- **Padding (P)**: Preserves dimensions using 'same' or reduces them with 'valid'.
- **Depth (D)**: Number of filters applied – outputs a volume, not a flat vector.

$$\text{Output Size} = \left\lfloor \frac{W - F + 2P}{S} \right\rfloor + 1$$

Example: 5x5 Input, 3x3 Filter, No Padding, Stride 1

- Output = $(5 - 3 + 0)/1 + 1 = 3$
- Resulting feature map = 3×3

Common Pitfall

Incorrect stride or padding can lead to mismatched input/output dimensions in deep CNN stacks.

Implementing Convolution in Keras

2D Convolution Layer in Keras

```
from tensorflow.keras.layers import Conv2D
from tensorflow.keras.models import Sequential

model = Sequential()
model.add(Conv2D(filters=32,
                 kernel_size=(3, 3),
                 strides=(1, 1),
                 padding='same',
                 activation='relu',
                 input_shape=(28, 28, 1)))

model.summary()
# Output shape: (None, 28, 28, 32)
```

Output Explanation

This layer outputs 32 feature maps of size 28x28, due to 'same' padding.

Why Shared Weights Matter

Traditional ANN: Every neuron has a unique set of weights.
CNN: Each kernel is used across the entire image (weight sharing).

$$\text{Total parameters} = (F \times F \times \text{Channels}) \times \text{Number of Filters}$$

Parameter Efficiency

CNNs drastically reduce the number of trainable parameters, enabling deeper models and faster training.

Example:

A 3×3 kernel on a single-channel image has $3 \times 3 = 9$ weights, regardless of image size.

Misconception

Weight sharing does not mean fewer computations – it only reduces parameters, not FLOPs.

Summary Table: Convolutional Layers and Kernel Operations

Concept	Explanation
Kernel / Filter	A small weight matrix that moves across the image extracting local features.
Stride	Step size with which the kernel moves – affects output size.
Padding	'Same' keeps output size equal to input; 'Valid' reduces dimensions.
Weight Sharing	Kernel parameters reused across input space – fewer total weights.
Output Volume	For multiple filters, CNN outputs a 3D volume of feature maps.

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What Happens When Filters Don't Fit Perfectly?

Question: How do we handle cases when the filter size does not evenly divide the input image?

$$\text{Output size} = \left\lfloor \frac{W - F + 2P}{S} \right\rfloor + 1$$

Warning: Spatial Reduction

Without padding, convolving large kernels can rapidly shrink the image – making it unusable in deep CNNs.

Two padding modes commonly used:

- **'valid'**: No padding – output shrinks.
- **'same'**: Pads input so that output size equals input size.

Why Padding Matters

Padding allows deeper models by maintaining spatial resolution, especially in early layers.

Understanding 'valid' Padding

'valid' padding means no padding at all:

$$\text{Output size} = \left\lfloor \frac{W - F}{S} \right\rfloor + 1$$

Example: 7x7 Input, 3x3 Filter, Stride 1, 'valid'

- Output size = $\left\lfloor \frac{7-3}{1} \right\rfloor + 1 = 5$
- Output feature map = 5×5

Drawback

Each convolution shrinks the feature map, which can lead to loss of border information.

Understanding ’same’ Padding

’same’ padding ensures that output dimensions match input:

$$P = \left\lfloor \frac{F-1}{2} \right\rfloor \quad \text{(for odd-sized filters)}$$

Goal: Maintain output size = input size

Example: 7x7 Input, 3x3 Filter, Stride 1, ’same’

- Padding = $\left\lfloor \frac{3-1}{2} \right\rfloor = 1$
- Output = $\left\lfloor \frac{7-3+2\cdot 1}{1} \right\rfloor + 1 = 7$

Use Case

Use ’same’ padding in early layers to retain spatial resolution for deep stacking.

Stride: The Step of Convolution

Stride (S) defines how far the filter jumps with each move.

- **Stride = 1:** Dense scanning of input.
- **Stride > 1:** Downsamples spatial dimensions.

$$\text{Output size} = \left\lfloor \frac{W - F + 2P}{S} \right\rfloor + 1$$

Example: 7x7 Input, 3x3 Filter, Padding = 0, Stride = 2

$$\left\lfloor \frac{7-3+0}{2} \right\rfloor + 1 = 3 \Rightarrow \text{Output size} = 3 \times 3$$

Oversized Strides

Large strides may skip important features and lead to aliasing.

Stride and Padding in Keras

Experimenting with Stride and Padding

```python
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D

model = Sequential()

# SAME padding
model.add(Conv2D(16, (3,3), strides=(1,1), padding='same',
    input_shape=(28,28,1)))
# VALID padding
model.add(Conv2D(32, (3,3), strides=(2,2), padding='valid'))

model.summary()
# Layer 1 Output: (28, 28, 16)
# Layer 2 Output: (13, 13, 32)
```

What This Means

'SAME' preserved the input size; 'VALID' with stride 2 reduced spatial dimensions to almost half.

Summary Table: Padding and Stride

Parameter	Description
'valid' Padding	No padding; output is smaller than input.
'same' Padding	Adds padding so output size equals input size.
Stride = 1	Moves filter by 1 pixel; maximum overlap.
Stride > 1	Skips pixels; reduces spatial size.
Padding and stride interaction	Controls spatial resolution and computational load.

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Why Do We Pool in CNNs?

Motivation: After convolution, feature maps may still be large. Pooling helps:

- Reduce spatial dimensions
- Introduce spatial invariance (translation robustness)
- Control overfitting by downsampling

$$\text{Output size} = \left\lfloor \frac{W - F}{S} \right\rfloor + 1$$

Definition

Pooling is a downsampling operation applied over each feature map independently.

Types:

- Max Pooling
- Average Pooling
- Global Pooling

Max Pooling with Numerical Example

Max Pooling: Selects the maximum value from each window.
Input Feature Map (4x4):

$$\begin{bmatrix} 1 & 3 & 2 & 4 \\ 5 & 6 & 7 & 8 \\ 2 & 1 & 0 & 3 \\ 4 & 9 & 5 & 2 \end{bmatrix}$$

2x2 Pool, Stride 2 $\Rightarrow$ **Output (2x2):**

$$\begin{bmatrix} 6 & 8 \\ 9 & 5 \end{bmatrix}$$

Interpretation

The highest value in each 2×2 block is preserved; other details are discarded.

Average Pooling with Numerical Example

Average Pooling: Computes the average of values in each region.
Same 4x4 Input:

$$\begin{bmatrix} 1 & 3 & 2 & 4 \\ 5 & 6 & 7 & 8 \\ 2 & 1 & 0 & 3 \\ 4 & 9 & 5 & 2 \end{bmatrix}$$

2x2 Pool, Stride 2 $\Rightarrow$ **Output (2x2):**

$$\begin{bmatrix} 3.75 & 5.25 \\ 4 & 2.5 \end{bmatrix}$$

Use Case

Average pooling is often used in tasks requiring smooth spatial reduction (e.g. regression, heatmaps).

Note

Average pooling may blur out sharp features or edges.

Global Pooling Layers

Global Pooling:

- Instead of using a fixed window, apply pooling across the entire feature map.
- Reduces each feature map to a **single value**.

$$\text{Global Max Pooling:} \quad y = \max(X) \qquad \text{Global Average Pooling:} \quad y = \frac{1}{N}\sum_{i=1}^{N} x_i$$

When to Use

Used before the final classification layer to flatten feature maps without needing a dense layer.

Example:

Global max pooling on a 3×3 feature map:

$$\begin{bmatrix} 0.5 & 1.2 & 0.3 \\ 0.4 & 2.1 & 0.8 \\ 0.6 & 0.7 & 1.0 \end{bmatrix} \Rightarrow \max = 2.1$$

Pooling Layers in Keras

Using Max and Average Pooling in Keras

```python
from tensorflow.keras.layers import MaxPooling2D, AveragePooling2D,
    GlobalMaxPooling2D
from tensorflow.keras.models import Sequential

model = Sequential()
model.add(MaxPooling2D(pool_size=(2, 2), strides=2, padding='valid'))
model.add(AveragePooling2D(pool_size=(2, 2), strides=2,
    padding='valid'))
model.add(GlobalMaxPooling2D())

model.summary()
# Outputs:
# MaxPooling2D -> reduces spatial dimensions by 2
# AveragePooling2D -> same reduction
# GlobalMaxPooling2D -> outputs 1 value per feature map
```

Best Practice

Use max pooling for feature extraction in classification tasks; average pooling for smoother transitions.

Summary Table: Pooling Layers

Pooling Type	Behavior and Use Case
Max Pooling	Retains the most dominant value in each region; preserves edges.
Average Pooling	Computes the mean of values; useful for smooth generalization.
Global Max Pooling	Reduces each feature map to a scalar by selecting the max value.
Global Average Pooling	Computes average of each feature map; common in modern CNNs.
Stride	Determines how much to shift the pooling window; controls downsampling.

Current Section

How Does a CNN Learn?

Problem: How are weights in convolutional layers trained via gradients?
Two main phases in CNN training:

- **Forward Pass:** Compute outputs (activations) layer by layer.
- **Backward Pass:** Propagate loss gradients and update weights.

$$\text{Loss} = \mathscr{L}(y_{\text{true}}, y_{\text{pred}}) \qquad \text{Goal: minimize } \mathscr{L}$$

Chain Rule of Gradients

Backpropagation in CNNs applies the chain rule to each layer:

$$\frac{\partial \mathscr{L}}{\partial W} = \frac{\partial \mathscr{L}}{\partial a} \cdot \frac{\partial a}{\partial z} \cdot \frac{\partial z}{\partial W}$$

Where:

W = weights, z = pre-activation, a = activation, $\mathscr{L}$ = loss function.

Forward Pass in CNNs: Numerical Example

Assume:

- Input image: 3×3
- Kernel: 2×2
- Stride = 1, No Padding
- Activation = ReLU

Input X:

$$\begin{bmatrix} 1 & 2 & 0 \\ -1 & 3 & 1 \\ 2 & -2 & 4 \end{bmatrix} \qquad \text{Kernel } K: \begin{bmatrix} 1 & 0 \\ -1 & 2 \end{bmatrix}$$

Convolution (no activation): Top-left region:

$$1 \cdot 1 + 2 \cdot 0 + (-1) \cdot (-1) + 3 \cdot 2 = 1 + 0 + 1 + 6 = 8$$

Apply ReLU:

$$\max(0, 8) = 8$$

Result

The resulting output activation map is computed by sliding the kernel and applying ReLU at each step.

Backpropagation in CNNs: Gradient of the Kernel

Key Gradient Path:

$$\frac{\partial \mathscr{L}}{\partial K} = \sum \left(\frac{\partial \mathscr{L}}{\partial Y} \cdot \frac{\partial Y}{\partial K} \right)$$

Each kernel gradient is the convolution of the input patch and the error from the next layer.

Numerical Concept:

- Assume $\frac{\partial \mathscr{L}}{\partial Y} = 1$ at the position where we computed 8.
- The corresponding input patch:

$$\begin{bmatrix} 1 & 2 \\ -1 & 3 \end{bmatrix} \Rightarrow \text{This becomes the gradient update for the kernel.}$$

Gradient Accumulation

During backpropagation, gradients are accumulated for each kernel weight across all positions where the kernel is applied.

CNN Weight Update Step

Once gradients are computed, we apply an update step:

$$W_{\text{new}} = W - \eta \cdot \frac{\partial \mathscr{L}}{\partial W}$$

- η is the learning rate
- Gradients are computed using convolutional patches

Gradient Descent

CNNs use mini-batch gradient descent (or variants like Adam) to update convolutional kernel weights efficiently.

Numerical Instability Warning

Vanishing gradients may occur in deep networks, especially before batch normalization or when using sigmoid/tanh activations.

Forward & Backprop in Keras (Conceptual)

Training a CNN Model with Keras

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, Flatten, Dense

model = Sequential([
    Conv2D(8, (3,3), activation='relu', input_shape=(28,28,1)),
    Flatten(),
    Dense(10, activation='softmax')
])

model.compile(optimizer='adam',
     loss='sparse_categorical_crossentropy')
model.fit(X_train, y_train, epochs=3)
# Forward: conv -> relu -> dense
# Backward: gradients flow through layers and update weights
```

Keras Behavior

Keras automatically handles the backward pass using TensorFlowâs symbolic differentiation.

Summary Table: Forward and Backpropagation in CNNs

Step	Explanation
Forward Pass	Applies kernel over input, produces activation maps, computes predictions.
Loss Computation	Compares prediction to label using loss function (e.g. cross-entropy).
Backward Pass	Applies chain rule to propagate gradients layer-by-layer.
Kernel Gradient	Convolves error term with input patch to compute gradient for each weight.
Weight Update	Uses gradient descent to update kernel values.

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Why Use OpenCV in CNN Pipelines?

Problem: Deep learning models require standardized image formats and intensities.
OpenCV (cv2) is an efficient C++-backed library used for:

- Reading and displaying images
- Converting color spaces
- Resizing, normalizing, and thresholding
- Augmenting training data

Why OpenCV?

- Fast image I/O and processing
- Consistent preprocessing for training/inference
- Direct NumPy compatibility

$$\text{CNN Input:} \quad X \in \mathbb{R}^{H \times W \times C} \Rightarrow \text{Standardized via OpenCV}$$

Reading and Displaying Images

Loading Image with OpenCV

```python
import cv2

img = cv2.imread('image.jpg')        # Loads image in BGR format
cv2.imshow('Original Image', img)
cv2.waitKey(0)
cv2.destroyAllWindows()
```

Under the Hood

cv2.imread() returns a NumPy array of shape $(H, W, 3)$:

- 3 channels: Blue, Green, Red
- Data type: unsigned 8-bit integers, range [0, 255]

$$\text{Pixel Value at (x, y)} = \text{BGR triplet} = [B, G, R]$$

Note

Images are loaded in BGR format, not RGB – this affects color transformations.

Grayscale Conversion: What Actually Happens?

cv2.cvtColor() can convert a BGR image to grayscale:

Convert Color to Grayscale

```
gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
```

Mathematics Behind Grayscale

$$\text{Gray} = 0.114 \cdot B + 0.587 \cdot G + 0.299 \cdot R$$

- Based on human eye sensitivity
- Emphasizes green, suppresses blue

Grayscale Conversion: What Actually Happens?

Numerical Example

For pixel: $[B, G, R] = [60, 120, 200]$:

$$\text{Gray} = 0.114 \cdot 60 + 0.587 \cdot 120 + 0.299 \cdot 200 = 6.84 + 70.44 + 59.8 = 137.08$$

$\Rightarrow \text{Rounded} = 137$

Caution

This is not a simple average – it is a perceptually weighted transformation.

Image Resizing: Scale Matters

Resizing an Image

```
resized = cv2.resize(gray, (64, 64), interpolation=cv2.INTER_AREA)
```

How It Works

Resizing interpolates pixel values to match target dimensions $(W_{\text{target}}, H_{\text{target}})$.

$$\text{Scaling Ratio} = \frac{W_{\text{target}}}{W_{\text{orig}}} \quad \text{New Pixel} = \text{Weighted average of surrounding pixels}$$

Example:

If resizing a 128×128 to 64×64, every 2×2 pixel block becomes one.

Interpolation Tip

Use `cv2.INTER_AREA` for shrinking and `cv2.INTER_CUBIC` or `INTER_LINEAR` for enlarging.

Pixel Normalization: From 0–255 to 0–1

Pixel Value Normalization

```
norm_img = resized / 255.0
```

Why Normalize?

- Neural nets train faster with smaller input ranges.
- Keeps gradients stable during backpropagation.

Example:

If pixel intensity = 137, then:

$$\text{Normalized} = \frac{137}{255} \approx 0.537$$

Note

CNNs assume input values in $[0, 1]$ or standardized (mean = 0, std = 1).

Complete Pipeline: From BGR to Normalized Tensor

Image Preprocessing Pipeline

```
import cv2
import numpy as np

img = cv2.imread('image.jpg')                          # BGR format
gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)           # Grayscale
resized = cv2.resize(gray, (64, 64))                   # Resize
norm = resized / 255.0                                 # Normalize

tensor = np.expand_dims(norm, axis=-1)                 # Shape: (64, 64,
    1)
```

Final Shape

CNNs expect inputs with shape (H, W, C) – for grayscale, $C = 1$.

Summary Table: OpenCV Preprocessing Techniques

Technique	**Mathematical Interpretation**
Grayscale Conversion	Weighted sum: $0.114B + 0.587G + 0.299R$
Resizing	Interpolated mapping from source to target pixel grid
Normalization	$I_{\text{norm}} = \frac{I}{255}$
Tensor Conversion	Ensures shape (H, W, C) by adding a channel axis

Current Section

Why Do We Augment Images in Deep Learning?

Motivation:

- CNNs can easily overfit on small datasets.
- Augmentation simulates new training samples.
- It improves generalization by exposing the model to more data variation.

Definition

Image augmentation applies transformations (e.g. rotation, scaling) to create altered versions of existing images.

$$\text{New Image} = T(I) \quad \text{where } T \text{ is a transformation matrix}$$

Warning

Augmentation only applies to training data – not to validation/test sets.

Geometric Transformations in OpenCV

Translation:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \end{bmatrix} \cdot \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Image Translation with OpenCV

```
import cv2
import numpy as np

tx, ty = 30, 20
M = np.float32([[1, 0, tx], [0, 1, ty]])
translated = cv2.warpAffine(img, M, (img.shape[1], img.shape[0]))
```

Numerical Example

Pixel at (50, 50) will move to $(50 + 30, 50 + 20) = (80, 70)$

Rotation in OpenCV

Rotation around the center:

$$M = \begin{bmatrix} \cos\theta & -\sin\theta & (1-\cos\theta)x_c + \sin\theta\, y_c \\ \sin\theta & \cos\theta & (1-\cos\theta)y_c - \sin\theta\, x_c \end{bmatrix}$$

Rotate an Image

```
center = (img.shape[1]//2, img.shape[0]//2)
M = cv2.getRotationMatrix2D(center, angle=45, scale=1.0)
rotated = cv2.warpAffine(img, M, (img.shape[1], img.shape[0]))
```

Numerical Example

Rotation by 45° moves point (1,0) to $(\cos 45^\circ, \sin 45^\circ) \approx (0.707, 0.707)$

Flipping, Scaling, and Zooming

Flipping:

cv2.flip(img, 1) $\Rightarrow$ Horizontal Flip   cv2.flip(img, 0) $\Rightarrow$ Vertical Flip

Scaling:

$$\text{Zoom matrix: } \begin{bmatrix} s & 0 & 0 \\ 0 & s & 0 \end{bmatrix}$$

Zooming with Resizing

```
zoomed = cv2.resize(img, None, fx=1.5, fy=1.5,
    interpolation=cv2.INTER_CUBIC)
```

Zoom Caveat

Cropping may be needed to maintain original size after zoom.

Keras: ‘ImageDataGenerator‘ and Random Augmentation

Use ‘ImageDataGenerator‘ for automatic augmentation during training:

Keras-Based Augmentation

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator

datagen = ImageDataGenerator(
    rotation_range=20,
    width_shift_range=0.2,
    height_shift_range=0.2,
    zoom_range=0.15,
    horizontal_flip=True,
    rescale=1./255
)

aug_iter = datagen.flow(X_train, y_train, batch_size=32)
```

Keras: ‘ImageDataGenerator‘ and Random Augmentation

How It Works

Each batch is randomly transformed using defined ranges – image dimensions remain consistent.

Example:

`rotation_range=20` allows rotation in $[-20^\circ, +20^\circ]$ uniformly at random.

Summary Table: Augmentation Techniques and Effects

Augmentation	**Mathematical Behavior / Purpose**
Rotation	Rotation matrix about image center
Translation	Pixel shift: $x' = x + t_x$, $y' = y + t_y$
Scaling (Zoom)	Multiplies pixel grid by scale factor s
Flipping	Flips image along axis (horizontal/vertical)
‘ImageDataGenerator‘	Randomly applies transformations per batch during training

Current Section

Why Extract Features Before CNNs?

Motivation: Before CNNs learn features automatically, classical methods used edge and corner detection to identify patterns.
Key classical features:

- **Edges** – indicate boundaries
- **Corners** – indicate intersection of edges
- **Gradients** – encode intensity change

$$\text{Edge strength} = \|\nabla I(x, y)\| = \sqrt{I_x^2 + I_y^2}$$

Why it matters

Classical filters like Canny or Sobel can reveal important patterns and be used in preprocessing, debugging, or feature engineering.

Sobel Edge Detection

Sobel operator estimates image gradients in x and y directions.

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}, \quad G_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

Gradient magnitude: $\sqrt{(G_x * I)^2 + (G_y * I)^2}$

Sobel Edge Detection in OpenCV

```
sobel_x = cv2.Sobel(gray, cv2.CV_64F, 1, 0, ksize=3)
sobel_y = cv2.Sobel(gray, cv2.CV_64F, 0, 1, ksize=3)
edges = np.sqrt(sobel_x**2 + sobel_y**2)
```

Numerical Insight

Gradient is strongest where pixel intensity changes rapidly in horizontal or vertical directions.

Canny Edge Detection: A Multi-Step Process

Steps of Canny:

1. Smooth image using Gaussian blur
2. Compute gradients (Sobel)
3. Apply non-maximum suppression
4. Hysteresis thresholding

Canny Edge Detection in OpenCV

```
edges = cv2.Canny(gray, threshold1=100, threshold2=200)
```

Thresholding Logic

- **Strong edges** > threshold2
- **Weak edges** > threshold1 but < threshold2
- Connected weak edges are kept; isolated ones are discarded

Important

Canny includes non-linear steps – not just simple filtering!

Harris Corner Detection

Corner: region where intensity changes in both x and y directions.
Harris Response Function:

$$R = \det(M) - k \cdot (\mathrm{trace}(M))^2$$

where M is the second-moment matrix:

$$M = \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

Harris Corners in OpenCV

```
gray_float = np.float32(gray)
harris = cv2.cornerHarris(gray_float, blockSize=2, ksize=3, k=0.04)
```

Interpretation

- $R \gg 0$: corner
- $R \approx 0$: flat region
- $R < 0$: edge

Visualizing Features and Annotations

Drawing Features on Image

```
# Mark Canny edges in red
img[edges > 100] = [0, 0, 255]

# Annotate corners
img[harris > 0.01 * harris.max()] = [0, 255, 0]

# Draw a rectangle or circle
cv2.rectangle(img, (10,10), (50,50), (255,0,0), 2)
cv2.circle(img, (60, 60), 10, (0, 255, 255), -1)
```

Why Visualize?

- Debug preprocessing steps
- Verify model interprets relevant structures
- Annotate features for inspection

Summary Table: Feature Detection Methods

Method	Mathematical Operation and Use
Sobel	Computes $\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y}$ to estimate edges
Canny	Multi-step pipeline: blur, Sobel, non-max suppression, thresholding
Harris Corners	Measures intensity variation using matrix eigenvalues
Feature Visualization	Overlay results to inspect edge/corner quality and position

Current Section

Complete Workflow: From Raw Image to Prediction

Objective: Use OpenCV to preprocess images, then train a CNN on MNIST/CIFAR-10 using TensorFlow.
Pipeline Steps:

1. Load image using OpenCV
2. Preprocess: grayscale, resize, normalize
3. Reshape for CNN input
4. Define and compile CNN model
5. Train and evaluate

$$X_{\text{CNN}} = \texttt{OpenCV(img)} \rightarrow \text{resize} \rightarrow \text{normalize} \rightarrow \text{expand\_dims}$$

Target Shape

CNN expects input shape: (N, H, W, C)

Preprocessing Pipeline Using OpenCV

OpenCV Preprocessing Function

```python
def preprocess_image(path, target_size=(32, 32)):
    img = cv2.imread(path)
    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
    resized = cv2.resize(gray, target_size)
    norm = resized / 255.0
    tensor = np.expand_dims(norm, axis=-1)
    return tensor
```

Numerical Example

Original: 128x128 RGB â Grayscale â Resize to 32x32 â Normalize â Add channel axis â (32, 32, 1)

Integration Ready

This function can be used in custom datasets, not just built-in Keras ones.

MNIST CNN Model with TensorFlow

CNN for MNIST (Grayscale)

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten,
     Dense, Dropout
model = Sequential([
    Conv2D(32, (3,3), activation='relu', input_shape=(28, 28, 1)),
    MaxPooling2D((2,2)),
    Conv2D(64, (3,3), activation='relu'),
    MaxPooling2D((2,2)),
    Flatten(),
    Dense(128, activation='relu'),
    Dropout(0.5),
    Dense(10, activation='softmax')
])
model.compile(optimizer='adam',
     loss='sparse_categorical_crossentropy', metrics=['accuracy'])
```

Why It Works

- Two conv-pool blocks
- Dense + dropout layer to control overfitting
- Output: 10 classes (digits 0–9)

CIFAR-10 CNN Model (RGB)

CNN for CIFAR-10 (Color)

```
model = Sequential([
    Conv2D(32, (3,3), activation='relu', input_shape=(32, 32, 3)),
    Conv2D(32, (3,3), activation='relu'),
    MaxPooling2D(pool_size=(2,2)),
    Dropout(0.25),

    Conv2D(64, (3,3), activation='relu'),
    MaxPooling2D(pool_size=(2,2)),
    Dropout(0.25),

    Flatten(),
    Dense(512, activation='relu'),
    Dropout(0.5),
    Dense(10, activation='softmax')
])
```

Design Insight

Deeper than MNIST model due to complexity of color images and 10 general object classes.

Train, Evaluate, and Integrate

Compile and Train Model

```
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
model.fit(X_train, y_train, batch_size=64, epochs=10,
     validation_split=0.2)
```

Model Evaluation

Use `model.evaluate()` to test on unseen data. You can also use OpenCV-processed inputs.

OpenCV + CNN Integration

You can feed any OpenCV-processed image directly into a trained CNN:

```
x = preprocess_image('custom_image.jpg', (28,28))
x = np.expand_dims(x, axis=0)  # Add batch dim
prediction = model.predict(x)
```

Summary Table: TensorFlow + OpenCV CNN Pipeline

Step	Technique and Explanation
Load & Convert Image	OpenCV reads image in BGR; convert to grayscale or RGB
Resize & Normalize	Resize to fixed shape (28x28 or 32x32); normalize to [0,1]
CNN Model (MNIST)	2 Conv layers + 1 Dense; input shape (28,28,1)
CNN Model (CIFAR-10)	More conv/pool layers; input shape (32,32,3)
Evaluation	Predict class from OpenCV-preprocessed image