

CIFAR# Canadian Institute for Advanced Research.

CIFAR-10 is a widely used benchmark dataset in computer vision,
specifically for image classification tasks
→ 10 labels or categories

Total images # 60,000

The CIFAR-10 dataset

The CIFAR-10 dataset consists of 60000 32x32 colour images in 10 classes, with 6000 images per class. There are 50000 training images and 10000 test images.

The dataset is divided into five training batches and one test batch, each with 10000 images. The test batch contains exactly 1000 randomly-selected images from each class. The training batches contain the remaining images in random order, but some training batches may contain more images from one class than another. Between them, the training batches contain exactly 5000 images from each class.

Here are the classes in the dataset, as well as 10 random images from each:



$$\begin{aligned} \text{Total no. of images} &= 60,000 \text{ across 10 classes/categories} \\ \downarrow & \\ \boxed{32 \times 32} & \quad \left[\begin{array}{l} \text{Training dataset} \# 50,000 \rightarrow \frac{50,000}{10} = 5000 \text{ / class} \\ \text{Validation / Testing dataset} \# 10,000 \end{array} \right] \\ \downarrow & \\ \text{Balanced dataset} \Rightarrow \text{each class has 6000 images} & \\ \frac{60,000}{10} &= 6000 \text{ / class} \quad \downarrow \\ \frac{10,000}{10} &= 1000 \text{ / class} \end{aligned}$$

The classes are completely mutually exclusive. There is no overlap between automobiles and trucks. "Automobile" includes sedans, SUVs, things of that sort. "Truck" includes only big trucks. Neither includes pickup trucks.

↓
same type of image
can't be in two classes

↓
Automobiles don't include "big trucks"

CIFAR-10 dataset background

Created by: Alex Krizhevsky et. al.
↓

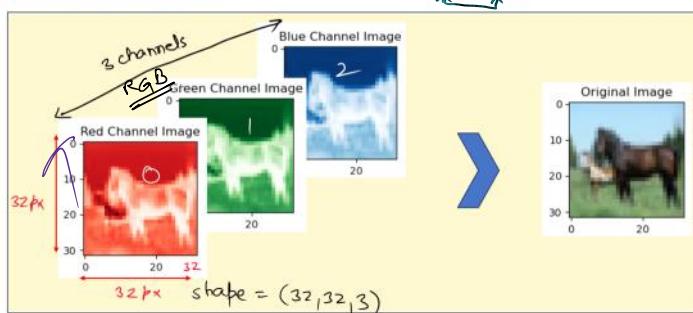
From source of 80 million images → (tiny) from MIT

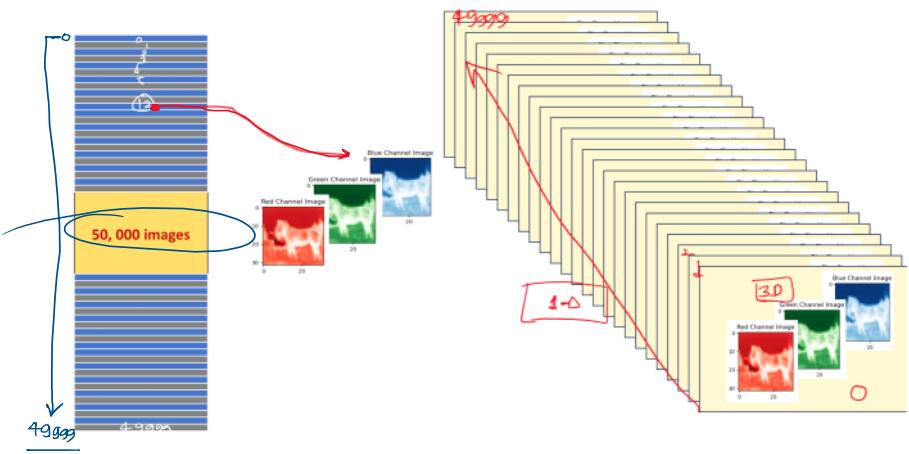
real world images from the web.
and then labelled it into 10 categories

Shape of the training images: (50000, 32, 32, 3)

3-dimensional view of the 13th image from the training dataset (out of 50,000 images)

13th (32, 32, 3)

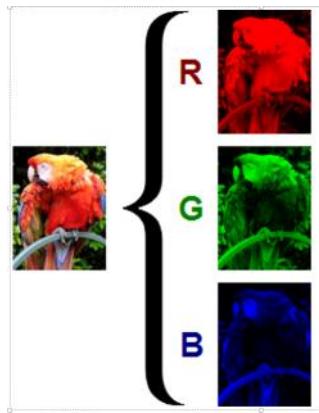
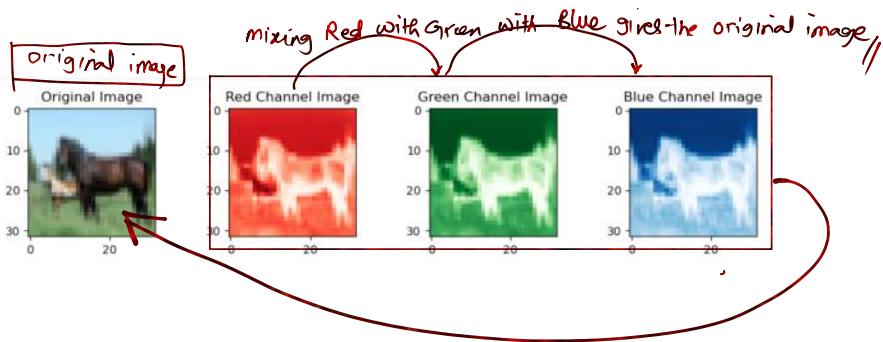


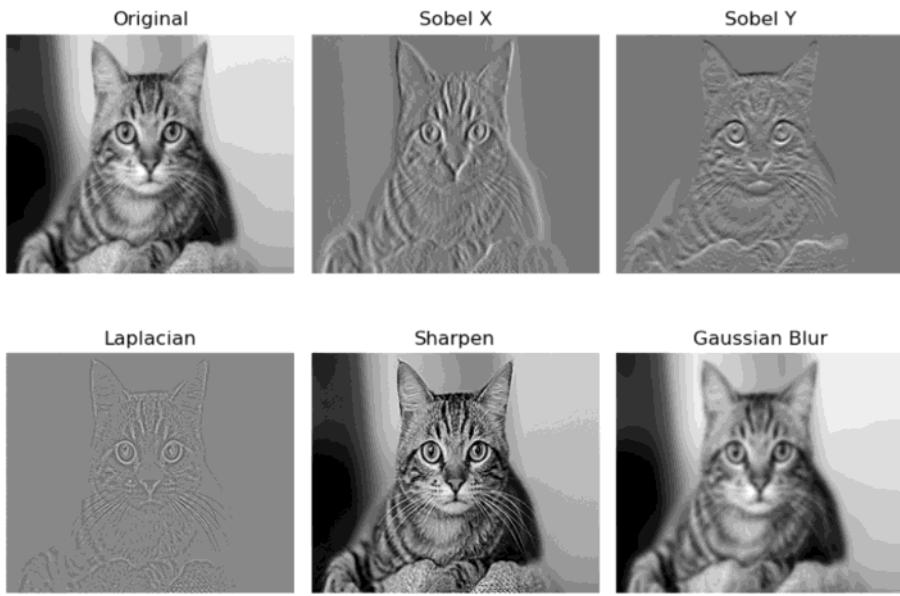


`train_images.shape`

(50000, 32, 32, 3)

```
: print("Dimension of training dataset is:", train_images.ndim)
Dimension of training dataset is: 4
```





UNDERSTANDING THE CONVOLUTION STEP (FILTERING)

SOBEL X vs SOBEL Y FILTERS



SOBEL operator is known to be classic **edge-detection filter** in image processing.

It works by convolving the image with two **3×3 kernels**

that approximate the **1st order derivative (gradient)**

in the **horizontal (X)** and **vertical (Y)** directions respectively

History: The SOBEL operator is named after Irwin Sobel – an American computer scientist

$$\text{SOBEL X: } \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \xrightarrow{\text{Transpose}} \text{SOBEL Y: } \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

Sobel X	Sobel Y
<ul style="list-style-type: none">- it detects vertical edges by emphasizing changes in the horizontal direction- left column has -ve values and right has +ve values- It highlights the regions where pixel intensities changes left to right	<ul style="list-style-type: none">- it detects horizontal edges by emphasizing changes in the vertical direction- Top row is -ve and bottom row is +ve.- It highlights regions where pixels intensity changes from top to bottom

LAPLACIAN FILTER

Original



Laplacian



- it is sometimes called Laplacian operator

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

Laplacian Operator

- it measures rate of change of gradients \rightarrow second order

derivative

$\frac{\partial}{\partial x}, \frac{\partial}{\partial y}$ 1st order derivative

gradient

\downarrow

$\frac{\partial}{\partial x} \left(\frac{\partial}{\partial x} \right) \rightarrow \frac{\partial^2}{\partial x^2}$

$\frac{\partial}{\partial y} \left(\frac{\partial}{\partial y} \right)$

rate of change

- In a region, it highlights the area where pixels' intensity changes \rightarrow edge in fine details, $\frac{\partial^2}{\partial y^2}$
and sometimes noise too

Note: Unlike SOBEL (directional), the Laplacian is isotropic.

↓
if detects edges in
all directions simultaneously

Two commonly used kernels (filters) for Laplacian filters:

1. 4-connected neighbors:

$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

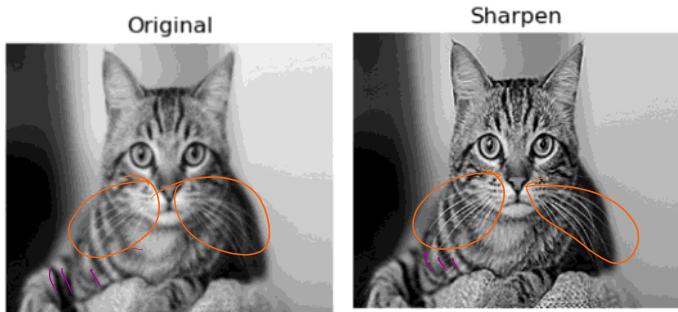
3×3

2. 8-connected neighbors:

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

Note: Laplacian filter is very sensitive to Noise!

SHARPEN FILTER



Observations

1. Edges such as fur lines, whiskers, paws, eyes are more pronounced.
 2. It provides the impression of more detail even though no new details were added.
- Sharpen filter enhances 'edges' and fine details by making the image crisper and by increasing contrast at the boundaries.

Common Filter / Kernel

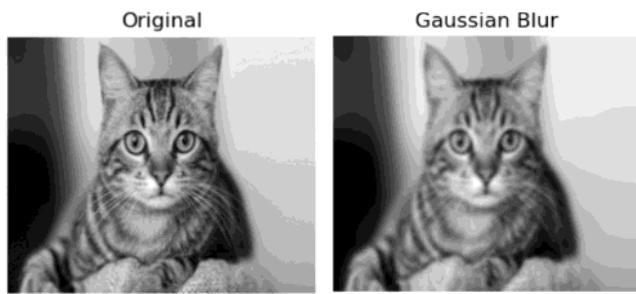
$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

central value of 5
intensifies the current pixel and neighbors subtract the edges' context → basically emphasizing the boundaries.

sharpener smooth



GAUSSIAN BLUR FILTER



- smoothens the image by averaging pixels based on Gaussian distribution
- it is used to reduce the noise, and smooth features before the edge detection

common filter example:

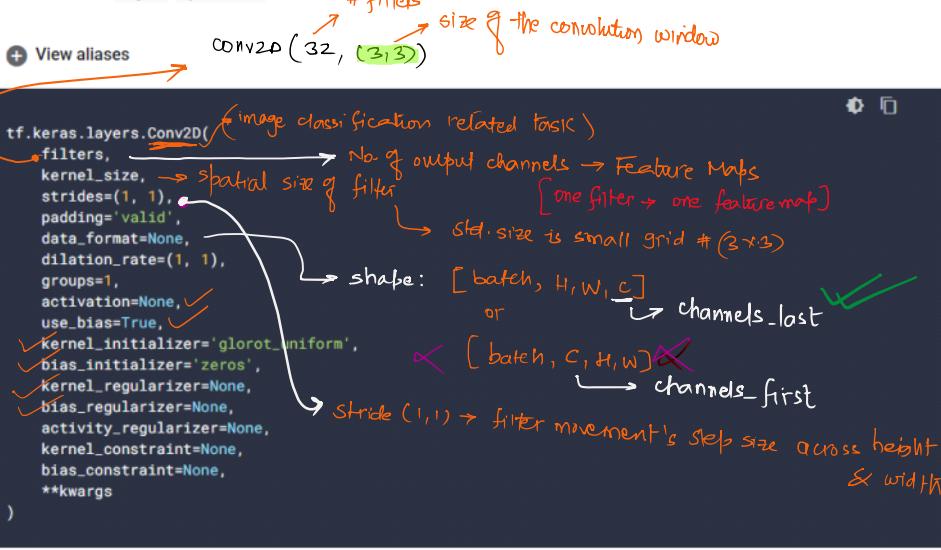
$$3 \times 3 \text{ kernel } (\sigma \approx 1) : \frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$

Filter	Purpose
Sobel X	→ it detects vertical edges
Sobel Y	→ it detects horizontal edges
Laplacian	→ all-directions → edge detection
sharpen	→ edge enhancement
Gaussian	→ Noise reduction.

tf.keras.layers.Conv2D

[View source on GitHub](#)

2D convolution layer.

Inherits From: [Layer](#), [Operation](#)Kernel-size can be **Square** or non-square grid.

Conv2D (32, (3,3)) ✓

or
Conv2D (32, (3,1))**padding='valid'**,↳ by default padding is **'valid'**

(No padding)

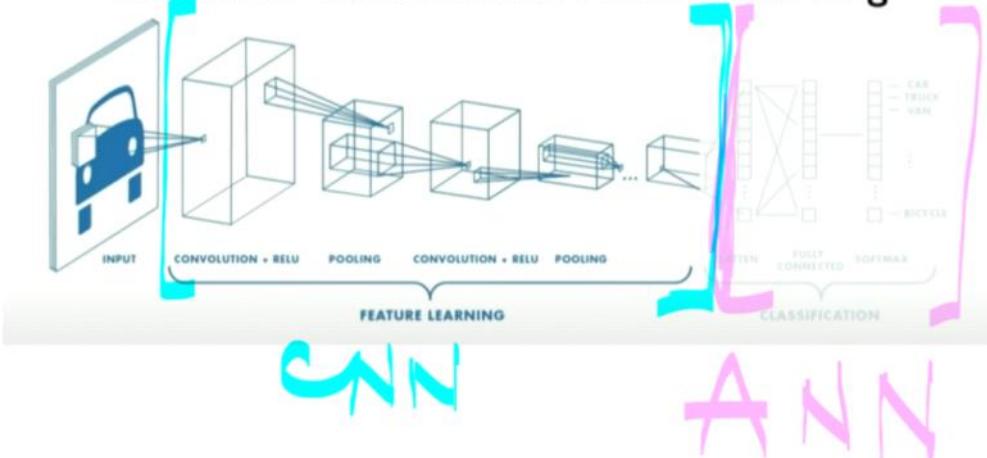
padding = 'same'

↳ zero padding to maintain the output size equal to input size

feature map size = Input image size (output) (input)

padding same means

CNNs for Classification: Feature Learning



```
history_01 = base_model.fit(train_images, train_labels, epochs = 50, validation_data=(test_images, test_labels))
```

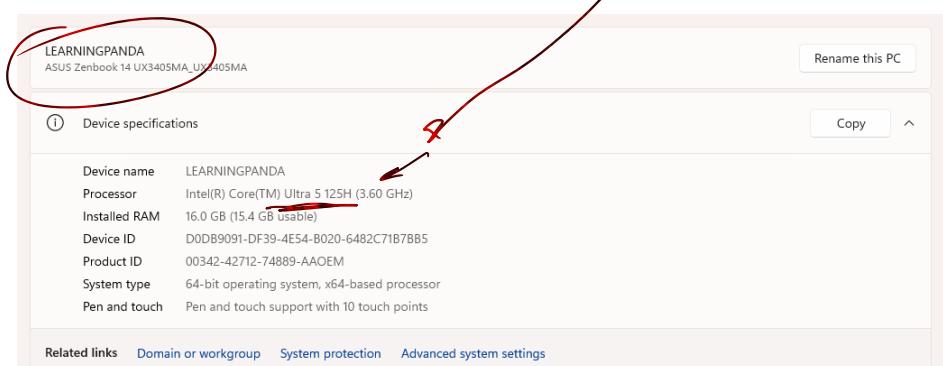
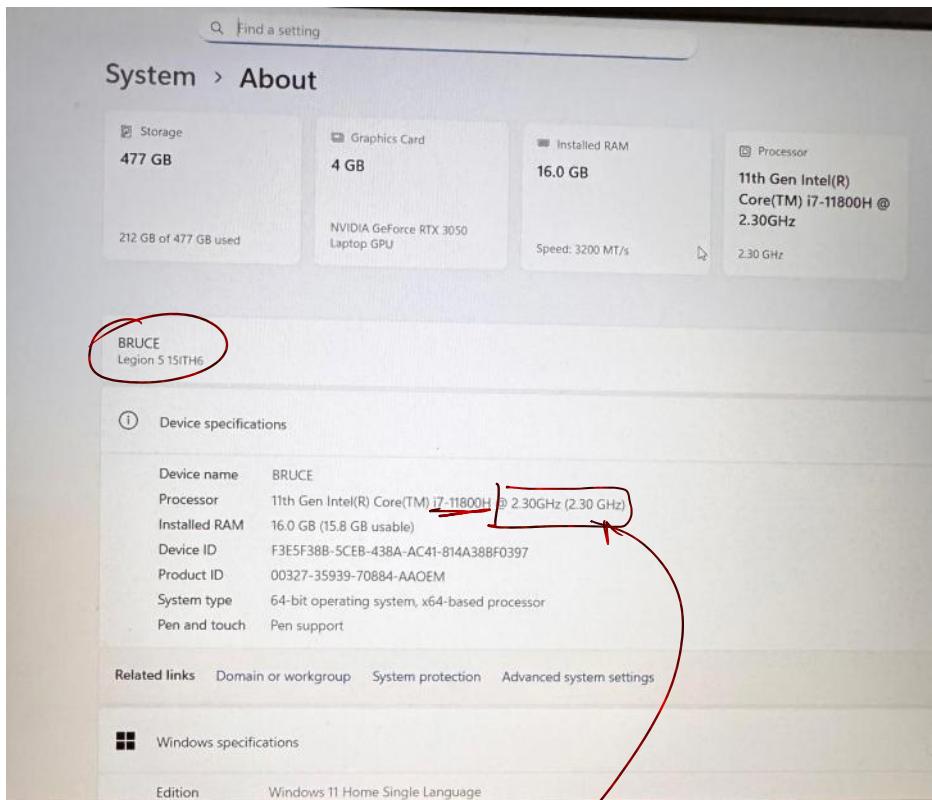
```
Epoch 1/50  
1563/1563 13s 7ms/step - accuracy: 0.3123 - loss: 2.9519 - val_accuracy: 0.4829 - val_loss: 1.4312  
Epoch 2/50  
1563/1563 13s 8ms/step - accuracy: 0.5166 - loss: 1.3621 - val_accuracy: 0.5465 - val_loss: 1.2675  
Epoch 3/50  
1563/1563 11s 7ms/step - accuracy: 0.5650 - loss: 1.2288 - val_accuracy: 0.5933 - val_loss: 1.1636  
Epoch 4/50  
1563/1563 11s 7ms/step - accuracy: 0.6161 - loss: 1.0847 - val_accuracy: 0.5876 - val_loss: 1.1713  
Epoch 5/50  
1563/1563 12s 8ms/step - accuracy: 0.6522 - loss: 0.9927 - val_accuracy: 0.6401 - val_loss: 1.0564  
Epoch 6/50  
1563/1563 12s 7ms/step - accuracy: 0.6782 - loss: 0.9280 - val_accuracy: 0.6290 - val_loss: 1.0882  
Epoch 7/50
```

'Legion'

Gaming laptop

```
history_01 = base_model.fit(train_images, train_labels, epochs = 50, validation_data = (test_images, test_labels))
```

```
Epoch 1/50  
1563/1563 - 52s 29ms/step - accuracy: 0.1200 - loss: 2.9709 - val_accuracy: 0.3599 - val_loss: 1.7135  
Epoch 2/50  
1563/1563 - 38s 24ms/step - accuracy: 0.4096 - loss: 1.6014 - val_accuracy: 0.5230 - val_loss: 1.3263  
Epoch 3/50  
1563/1563 - 20s 13ms/step - accuracy: 0.5367 - loss: 1.3065 - val_accuracy: 0.5538 - val_loss: 1.2627  
Epoch 4/50
```



```

Epoch 31/50
1563/1563 42s 27ms/step - accuracy: 0.8961 - loss: 0.3054 - val_accuracy: 0.6291 - val_loss: 2.1242
Epoch 32/50
1563/1563 52s 34ms/step - accuracy: 0.8968 - loss: 0.3048 - val_accuracy: 0.6315 - val_loss: 2.1665
Epoch 33/50
1563/1563 81s 52ms/step - accuracy: 0.9010 - loss: 0.3013 - val_accuracy: 0.6300 - val_loss: 2.1951
Epoch 34/50
1563/1563 46s 30ms/step - accuracy: 0.9016 - loss: 0.2964 - val_accuracy: 0.6343 - val_loss: 2.1024
Epoch 35/50
1563/1563 45s 29ms/step - accuracy: 0.8966 - loss: 0.3116 - val_accuracy: 0.6321 - val_loss: 2.3190
Epoch 36/50
1563/1563 57s 36ms/step - accuracy: 0.9079 - loss: 0.2803 - val_accuracy: 0.6280 - val_loss: 2.2500
Epoch 37/50
1563/1563 136s 87ms/step - accuracy: 0.9057 - loss: 0.2945 - val_accuracy: 0.6263 - val_loss: 2.4384
Epoch 38/50
1563/1563 150s 96ms/step - accuracy: 0.9080 - loss: 0.2833 - val_accuracy: 0.6230 - val_loss: 2.3281
Epoch 39/50
1563/1563 189s 87ms/step - accuracy: 0.9076 - loss: 0.2885 - val_accuracy: 0.6310 - val_loss: 2.2641
Epoch 40/50
1563/1563 177s 113ms/step - accuracy: 0.9139 - loss: 0.2635 - val_accuracy: 0.6287 - val_loss: 2.3339
Epoch 41/50
1563/1563 204s 114ms/step - accuracy: 0.9116 - loss: 0.2736 - val_accuracy: 0.6281 - val_loss: 2.4073
Epoch 42/50
1563/1563 238s 137ms/step - accuracy: 0.9093 - loss: 0.2829 - val_accuracy: 0.6317 - val_loss: 2.4319
Epoch 43/50
1563/1563 218s 108ms/step - accuracy: 0.9121 - loss: 0.2803 - val_accuracy: 0.6260 - val_loss: 2.4315
Epoch 44/50
1563/1563 123s 57ms/step - accuracy: 0.9162 - loss: 0.2635 - val_accuracy: 0.6247 - val_loss: 2.5641
Epoch 45/50

```

Base Model Run #1

Epochs # 50

training accuracy: 90% ↪
validation accuracy: 63% ↪

↓

conclusion: Model seems to be highly overfit,

EARLY STOPPING - will discuss about it