BSC~Microsoft Research Centre

Deep Learning for Computer Vision Tassadaq Hussain Professor Namal University Director Centre for AI and Big Data

Collaborations:

Barcelona Supercomputing Center Barcelona, Spain European Network on High Performance and Embedded Architecture and Compilation Pakistan Supercomputing Center



UCERD

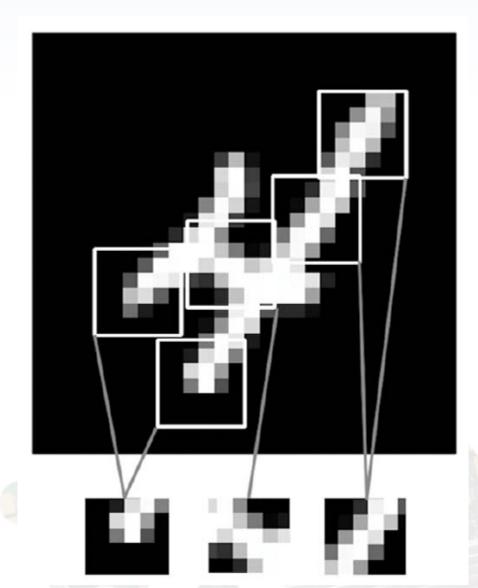
Gathering Intellectuals



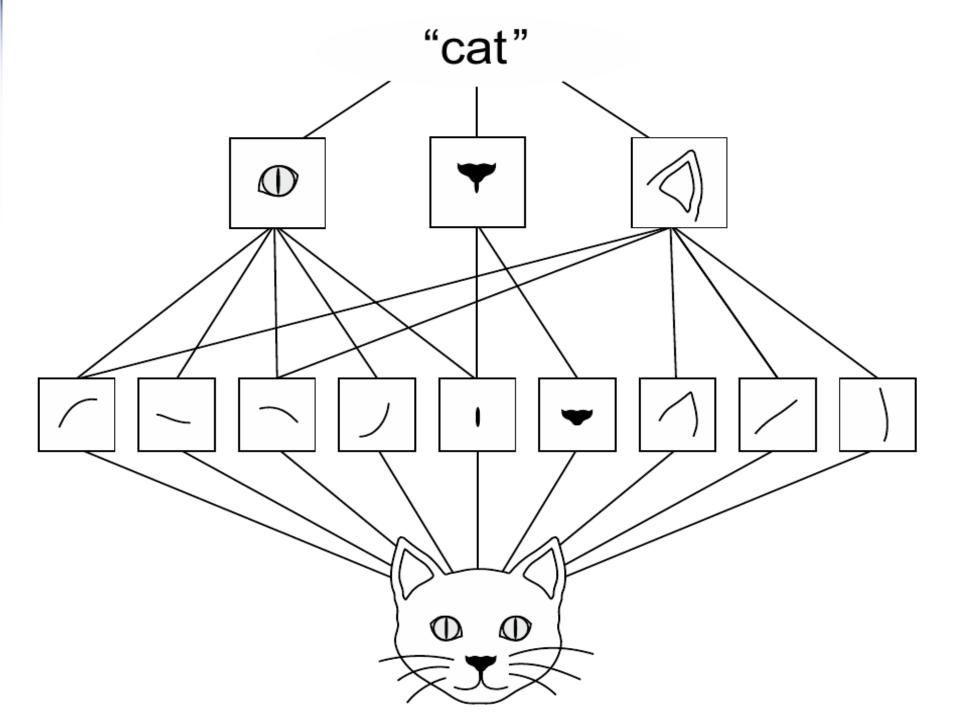
- from tensorflow import keras
- from tensorflow.keras import layers
- inputs = keras.Input(shape=(28, 28, 1))
- x = layers.Conv2D(filters=32, kernel_size=3, activation="relu")(inputs)
- x = layers.MaxPooling2D(pool_size=2)(x)
- x = layers.Conv2D(filters=64, kernel_size=3, activation="relu")(x)
- x = layers.MaxPooling2D(pool_size=2)(x)
- x = layers.Conv2D(filters=128, kernel_size=3, activation="relu")(x)
- x = layers.Flatten()(x)
- outputs = layers.Dense(10, activation="softmax")(x)
- model = keras.Model(inputs=inputs, outputs=outputs)

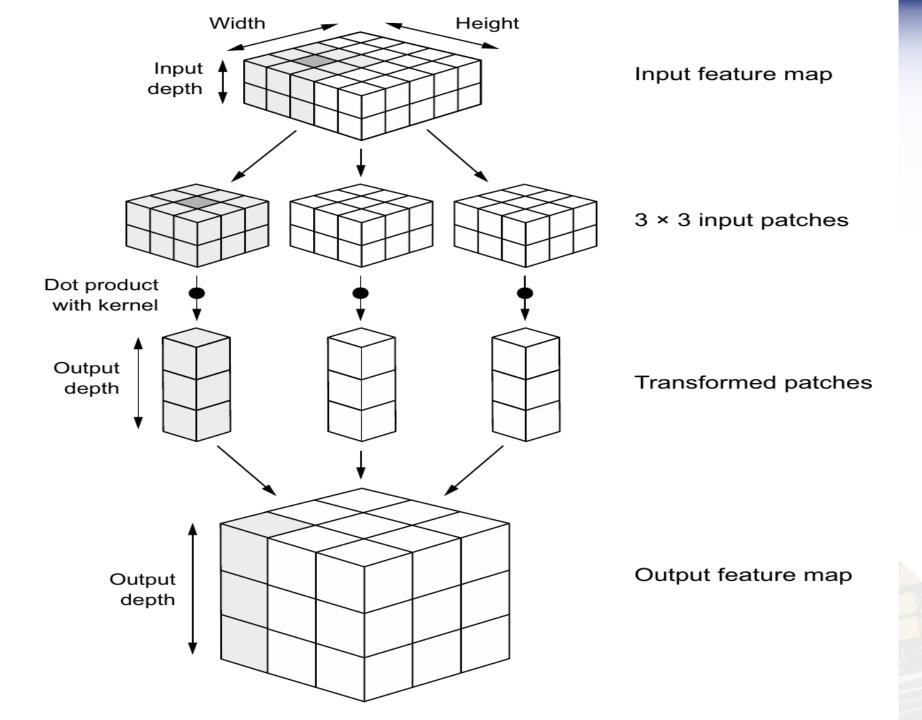


Convolution operation

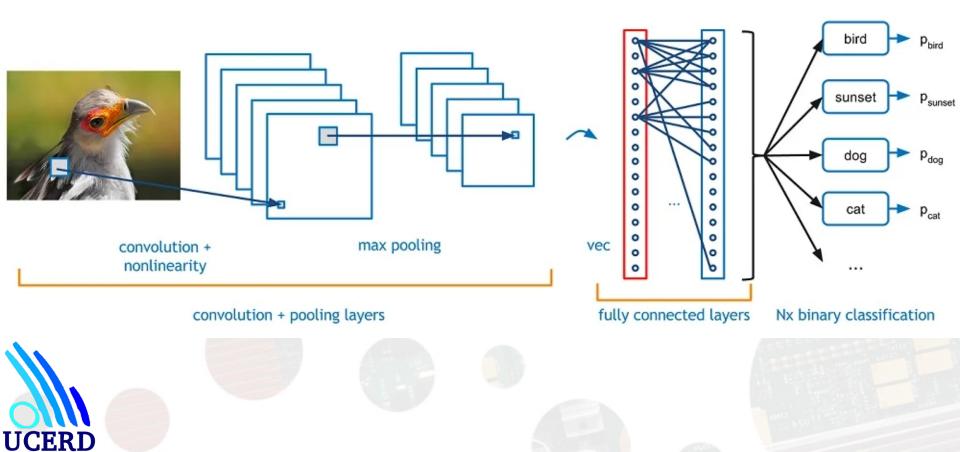










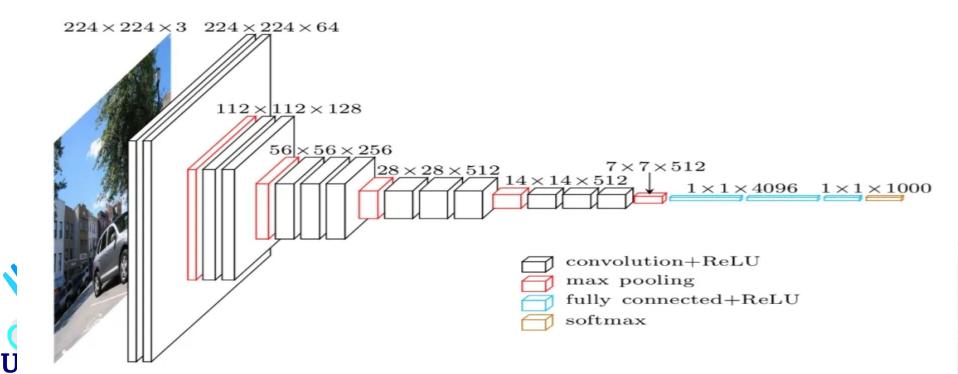


CNN?

 Computer vision is evolving rapidly day-by-day. Its one of the reason is deep learning. When we talk about computer vision, a term convolutional neural network(abbreviated as CNN) comes in our mind because CNN is heavily used here. Examples of CNN in computer vision are face recognition, image classification etc. It is similar to the basic neural network. CNN also have learnable parameter like neural network i.e. weights, biases etc.

Why CNN

- Suppose image is 1000 x 1000 which means you need 10⁶ neurons in input layer. It is computationally ineffective right.
- CNN extract the feature of image and convert it into lower dimension without loosing its characteristics.





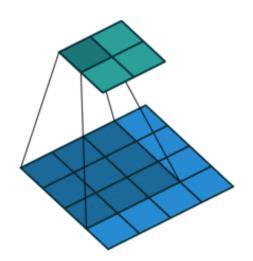


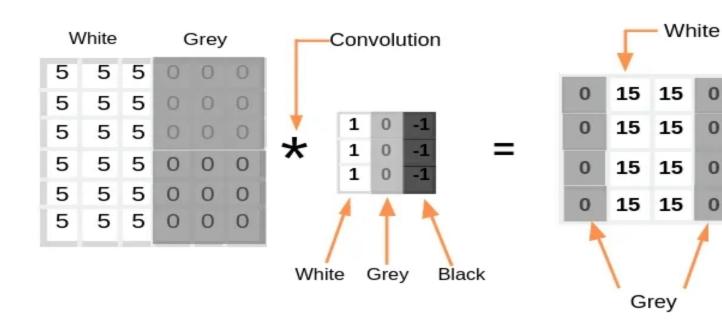


3 Channels



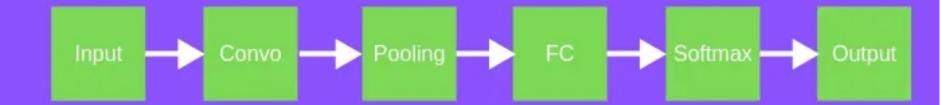
Edge Detection







Layers in CNN





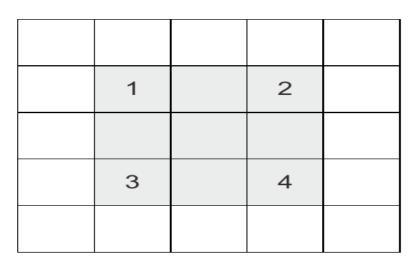
The convolution operation

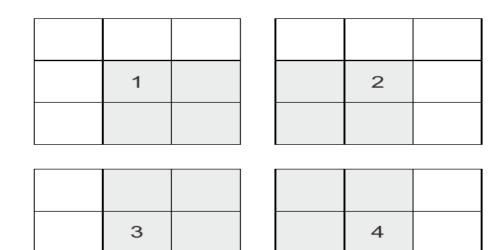
- The fundamental difference between a densely connected layer and a convolution layer is this:
- Dense layers learn global patterns in their input feature space
- Convolution layers learn local patterns in the case of images, patterns found in small 2D windows of the inputs.



CONVOLUTION STRIDES

- The other factor that can influence output size is the notion of strides.
- It has been assumed that the center tiles of the convolution windows are all contiguous. But the distance between two successive windows is a parameter of the convolution, called its stride, which defaults to 1.



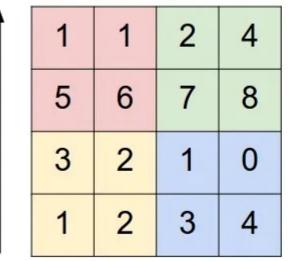


Activation Layer (ReLU):

After each convolutional operation, a nonlinear activation function, often ReLU (Rectified Linear Unit), is applied elementwise to introduce non-linearity into the model. ReLU helps in capturing complex patterns and relationships within the data.



Single depth slice



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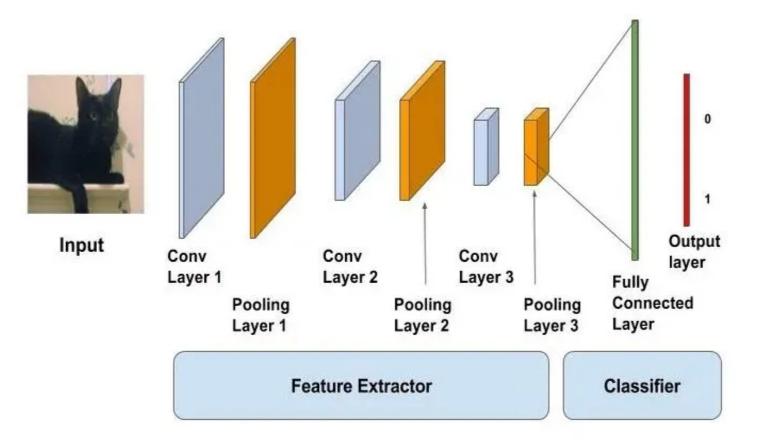
max pool with 2x2 filters and stride 2

6	8
3	4



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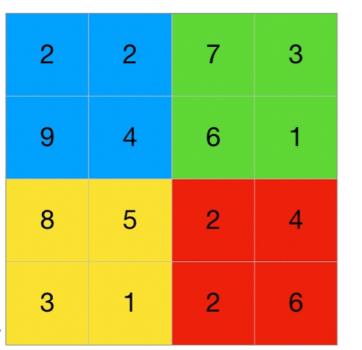


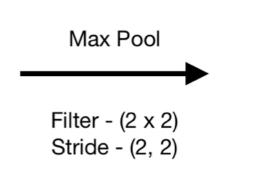


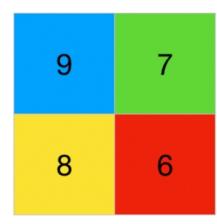


The max-pooling operation

 Pooling layers (e.g., MaxPooling or AveragePooling) are used to downsample the spatial dimensions of the feature maps generated by the convolutional layers. This reduces the computational load and helps in creating a more abstract representation of the input data.







Fully Connected Layer (Dense Layer):

Fully connected layers connect every neuron in one layer to every neuron in the next layer. They are typically placed towards the end of the CNN and are responsible for making predictions based on the high-level features extracted by the earlier layers.



Flattening Layer:

Before passing the output of the convolutional and pooling layers to the fully connected layers, a flattening layer is often used to convert the 2D matrix data into a vector. This step prepares the data for input into the fully connected layers.

Output Layer:

The output layer produces the final predictions or classifications. The number of neurons in this layer corresponds to the number of classes in a classification task, and the activation function is often softmax for multi-class classification.



from tensorflow import keras

- from tensorflow.keras import layers
- inputs = keras.Input(shape=(180, 180, 3))
- x = layers.Rescaling(1./255)(inputs)
- x = layers.Conv2D(filters=32, kernel_size=3, activation="relu")(x)
- x = layers.MaxPooling2D(pool_size=2)(x)
- x = layers.Conv2D(filters=64, kernel_size=3, activation="relu")(x)
- x = layers.MaxPooling2D(pool_size=2)(x)
- x = layers.Conv2D(filters=128, kernel_size=3, activation="relu")(x)
- x = layers.MaxPooling2D(pool_size=2)(x)
- x = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
- x = layers.MaxPooling2D(pool_size=2)(x)
- x = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
- x = layers.Flatten()(x)

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- outputs = layers.Dense(1, activation="sigmoid")(x)
 - model = keras.Model(inputs=inputs, outputs=outputs)



cats vs dogs small/ ...train/cat/dog/ ...validation/cat/dog/ ...test/cat/dog/

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Contains 1,000 cat images

Contains 1,000 dog images

Contains 500 cat images

Contains 500 dog images

Contains 1,000 cat images



```
import os, shutil, pathlib
original dir = pathlib.Path("train")
new base dir = pathlib.Path("cats vs dogs small")
def make subset(subset name, start index, end index):
for category in ("cat", "dog"):
dir = new base dir / subset name / category
os.makedirs(dir)
fnames = [f"{category}.{i}.jpg"
for i in range(start index, end index)]
for fname in fnames:
shutil.copyfile(src=original_dir / fname,
dst=dir / fname)
make subset("train", start index=0, end index=1000)
make subset("validation", start index=1000, end index=1500)
make subset("test", start index=1500, end index=2500)
```

