

5. Rețele neuronale convoluționale

5.1 Operația de convoluție

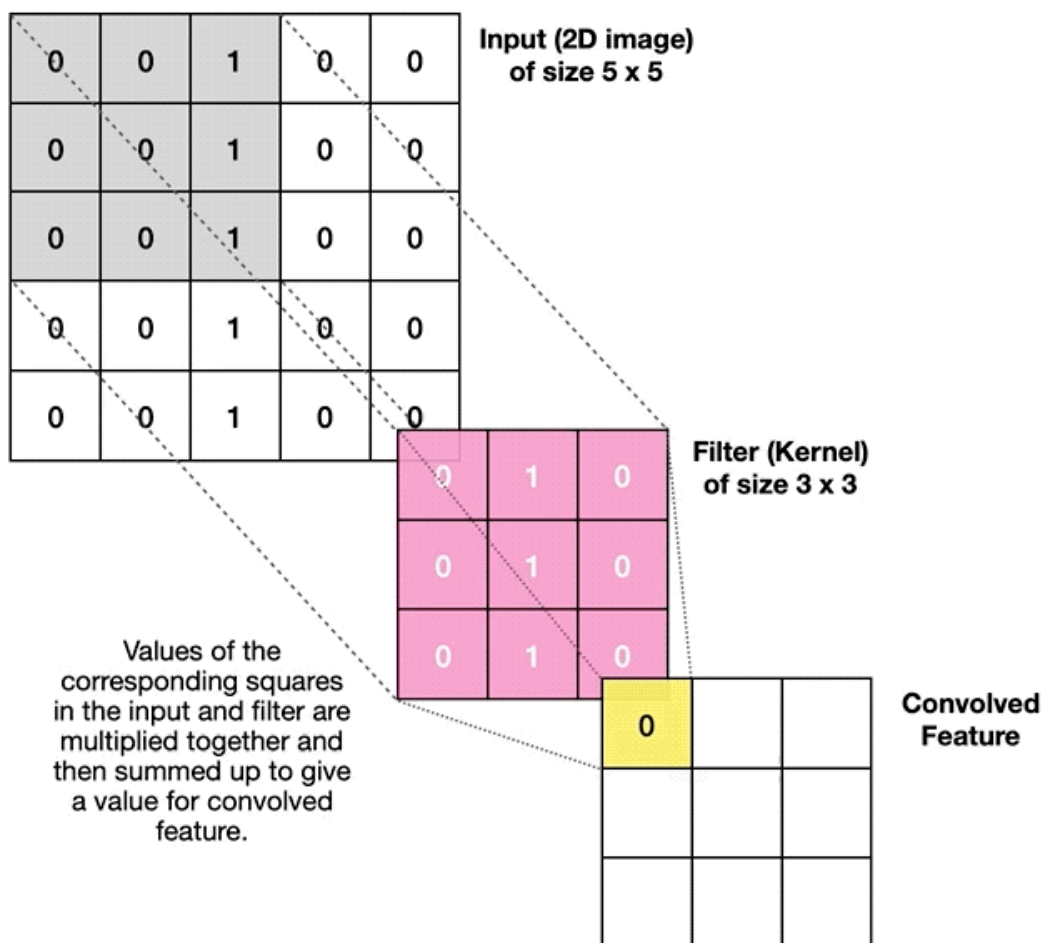


Fig. 5.1 Ilustrarea operației de convoluție (Dobilas, 2022)

5.2 Operația de subeșantionare

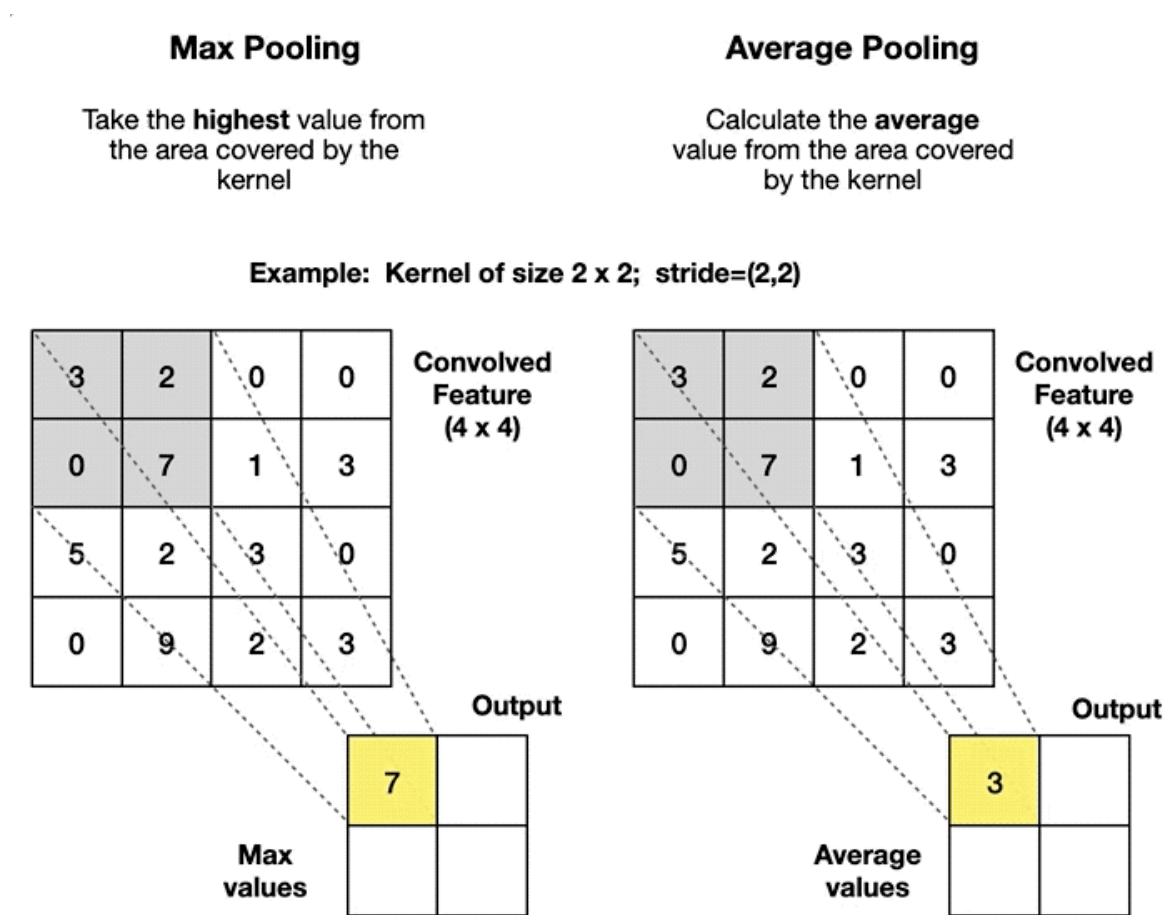


Fig. 5.2 Ilustrarea operației de subeșantionare (Dobilas, 2022)

5.3 Exemplificarea operației de convoluție

În continuare, vom exemplifica operația de convoluție folosind un strat convoluțional 2D.

input shape:

[samples, rows, columns, channels]

kernel shape:

[height, width, depth/input channels, output feature maps]

feature map shape:

```
[samples, rows, columns, filters]
```

```
import numpy as np
from keras import layers, models

input_image = np.zeros((8, 8), dtype='uint8')
input_image[:, 3:5] = 1
print(input_image)
```

```
[[0 0 0 1 1 0 0 0]
 [0 0 0 1 1 0 0 0]
 [0 0 0 1 1 0 0 0]
 [0 0 0 1 1 0 0 0]
 [0 0 0 1 1 0 0 0]
 [0 0 0 1 1 0 0 0]
 [0 0 0 1 1 0 0 0]
 [0 0 0 1 1 0 0 0]]
```

```
input_image = input_image[np.newaxis, ..., np.newaxis]
print(input_image.shape)
```

```
(1, 8, 8, 1)
```

```
model = models.Sequential()
model.add(layers.Conv2D(filters=1, kernel_size=(3, 3),
                        input_shape=input_image.shape[1:]))
```

```
kernel = np.array([[0, 1, 0], [0, 1, 0], [0, 1, 0]])
print(kernel)
```

```
[[0 1 0]
 [0 1 0]
 [0 1 0]]
```

```
kernel = kernel[..., np.newaxis, np.newaxis]
print(kernel.shape)
```

```
(3, 3, 1, 1)
```

```
weights = [kernel, np.array([0])]
```

```
model.set_weights(weights)
```

```
print(model.get_weights())
```

```
[array([[[[0.]],  
        [[1.]],  
        [[0.]]],  
       [[[0.]],  
        [[1.]],  
        [[0.]]],  
       [[[0.]],  
        [[1.]],  
        [[0.]]], dtype=float32), array([0.], dtype=float32)]
```

```
pred = model.predict(input_image)
```

```
print(pred.shape)
```

```
(1, 6, 6, 1)
```

```
for r in range(pred.shape[1]):  
    print([pred[0, r, c, 0] for c in range(pred.shape[2])])
```

```
[[0. 0. 3. 3. 0. 0.]  
 [0. 0. 3. 3. 0. 0.]  
 [0. 0. 3. 3. 0. 0.]  
 [0. 0. 3. 3. 0. 0.]  
 [0. 0. 3. 3. 0. 0.]  
 [0. 0. 3. 3. 0. 0.]
```

5.4 Vizualizarea filtrelor și a hărților de caracteristici

ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

VGG-16 model:

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 224, 224, 3)	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten (Flatten)	(None, 25088)	0

fc1 (Dense)	(None, 4096)	102764544
fc2 (Dense)	(None, 4096)	16781312
predictions (Dense)	(None, 1000)	4097000
=====		
Total params: 138,357,544		
Trainable params: 138,357,544		
Non-trainable params: 0		
=====		

The layer indexes of the last convolutional layer in each block are [2, 5, 9, 13, 17].

Vizualizarea filtrelor

```
from keras.applications.vgg16 import VGG16
import matplotlib.pyplot as plt
import seaborn as sns

model = VGG16(weights='imagenet', include_top=False)
model.summary()

for layer in model.layers:
    if 'conv' not in layer.name:
        continue
    filters, biases = layer.get_weights()
    print(layer.name, filters.shape)

filters, biases = model.layers[1].get_weights()
print(filters.shape)

sns.histplot(data=filters.flatten(), kde=True, stat='density')

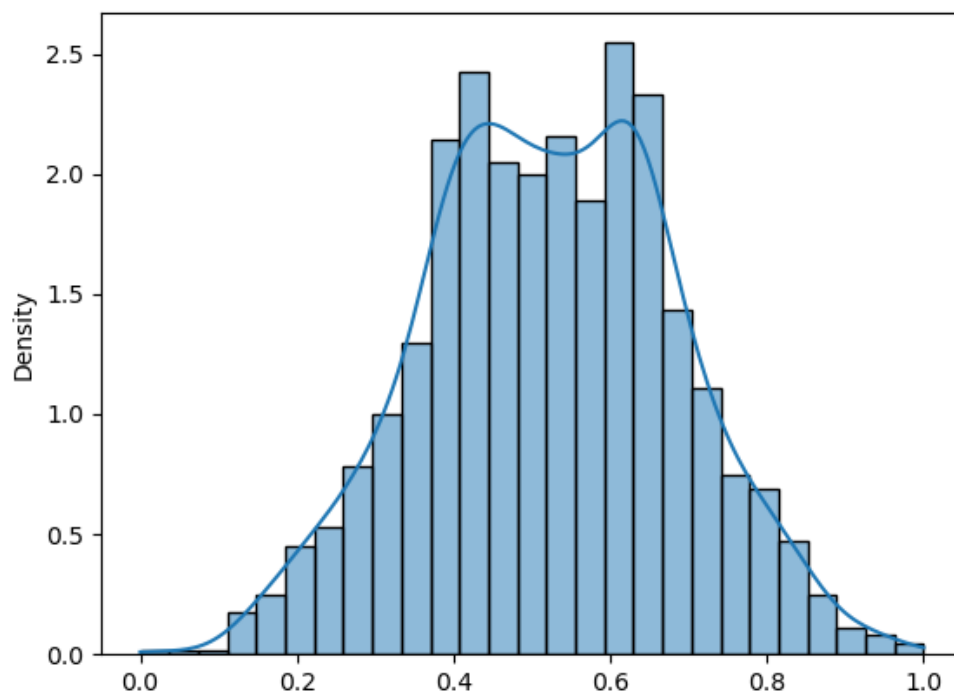
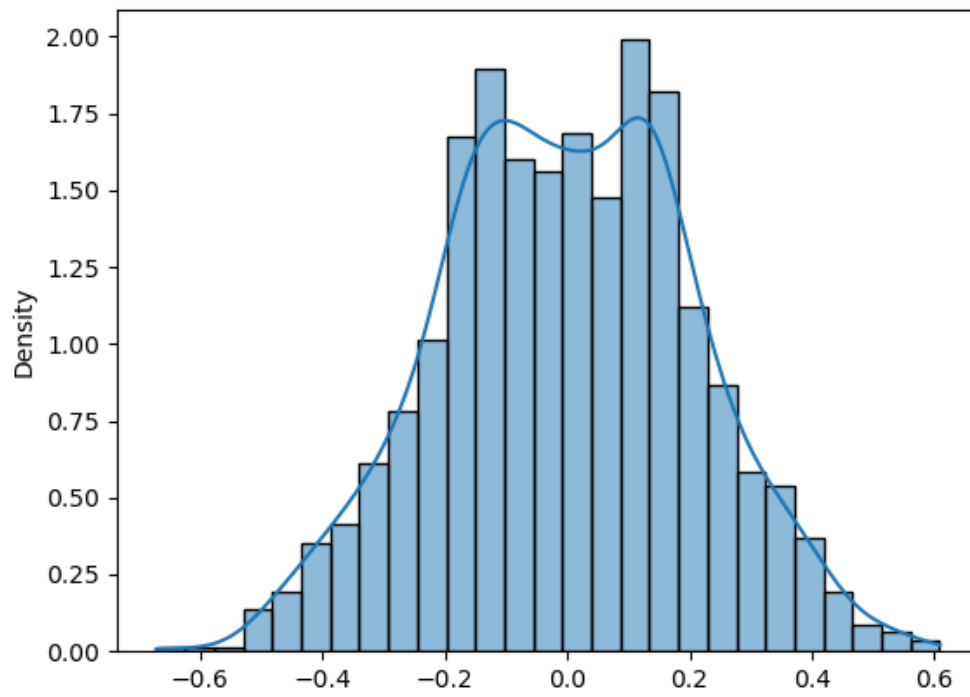
f_min, f_max = filters.min(), filters.max()
filters = (filters - f_min) / (f_max - f_min)

sns.histplot(data=filters.flatten(), kde=True, stat='density')

n_filters = 6
fig, axs = plt.subplots(nrows=n_filters, ncols=3,
                        figsize=(6, 8))
for i in range(n_filters):
    f = filters[:, :, :, i]
    for j in range(3):
        axs[i, j].imshow(f[:, :, j], cmap='gray')
        axs[i, j].set_xticks([])
        axs[i, j].set_yticks([])
plt.show()
```

```
block1_conv1 (3, 3, 3, 64)
block1_conv2 (3, 3, 64, 64)
block2_conv1 (3, 3, 64, 128)
block2_conv2 (3, 3, 128, 128)
block3_conv1 (3, 3, 128, 256)
block3_conv2 (3, 3, 256, 256)
block3_conv3 (3, 3, 256, 256)
block4_conv1 (3, 3, 256, 512)
block4_conv2 (3, 3, 512, 512)
block4_conv3 (3, 3, 512, 512)
block5_conv1 (3, 3, 512, 512)
block5_conv2 (3, 3, 512, 512)
block5_conv3 (3, 3, 512, 512)
```

(3, 3, 3, 64)



Vizualizarea hărților de caracteristici

```
from keras.applications.vgg16 import VGG16
from keras.applications.vgg16 import preprocess_input
from keras.preprocessing.image import load_img
from keras.preprocessing.image import img_to_array
from keras.models import Model
import matplotlib.pyplot as plt
import numpy as np

model = VGG16(weights='imagenet', include_top=False)

ixs = [2, 5, 9, 13, 17]
outputs = [model.layers[i].output for i in ixs]
model = Model(inputs=model.inputs, outputs=outputs)

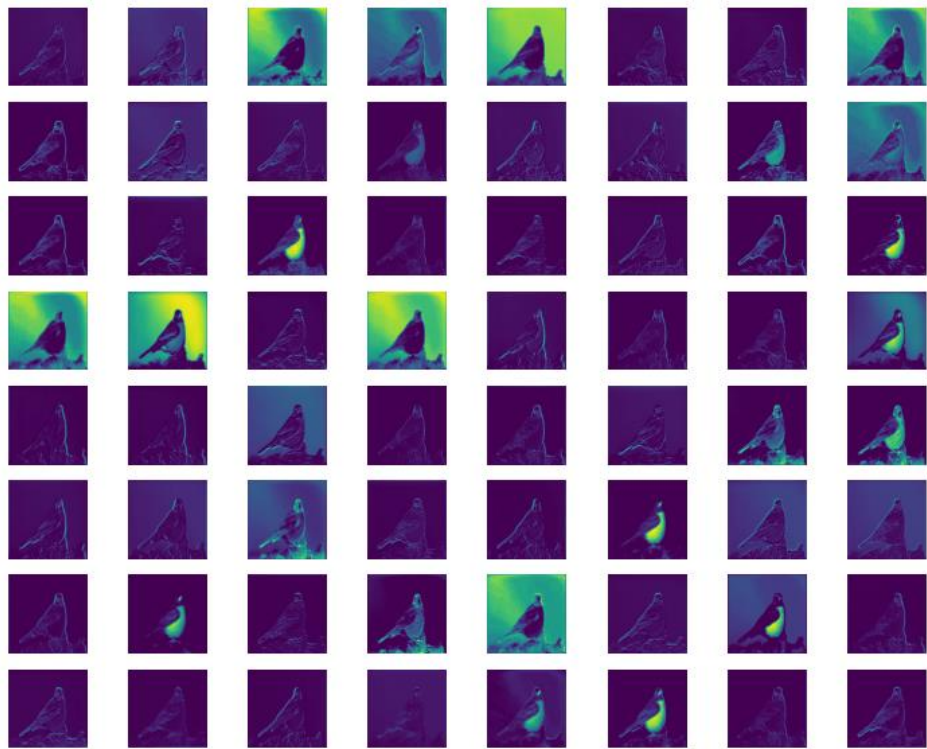
img = load_img('bird.jpg', target_size=(224, 224))
img = img_to_array(img)

img = np.expand_dims(img, axis=0)
img = preprocess_input(img)

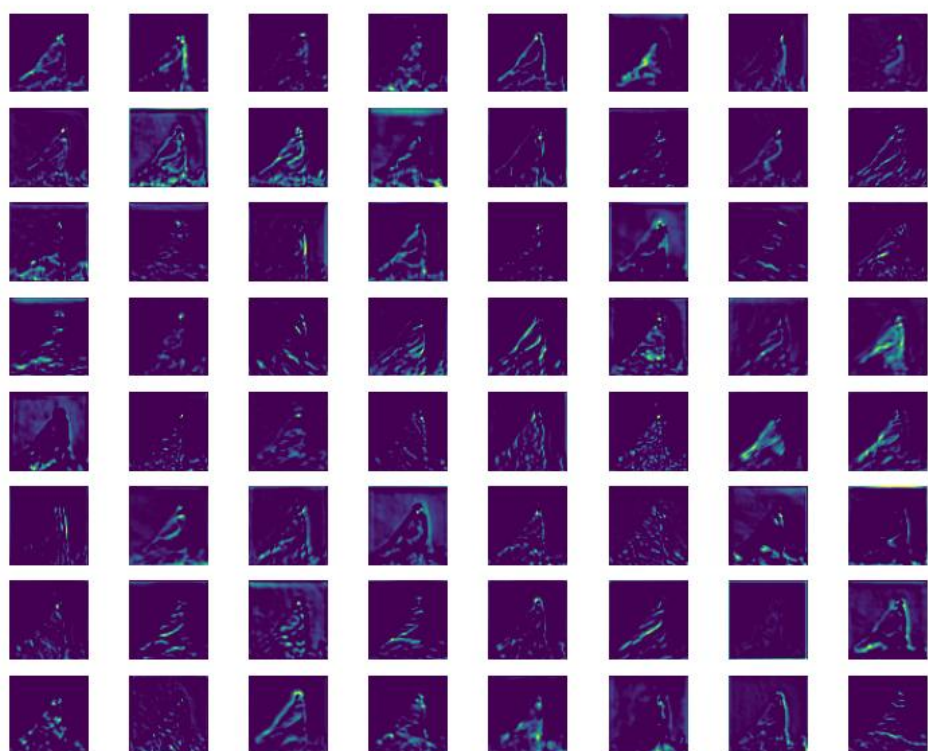
feature_maps = model.predict(img)

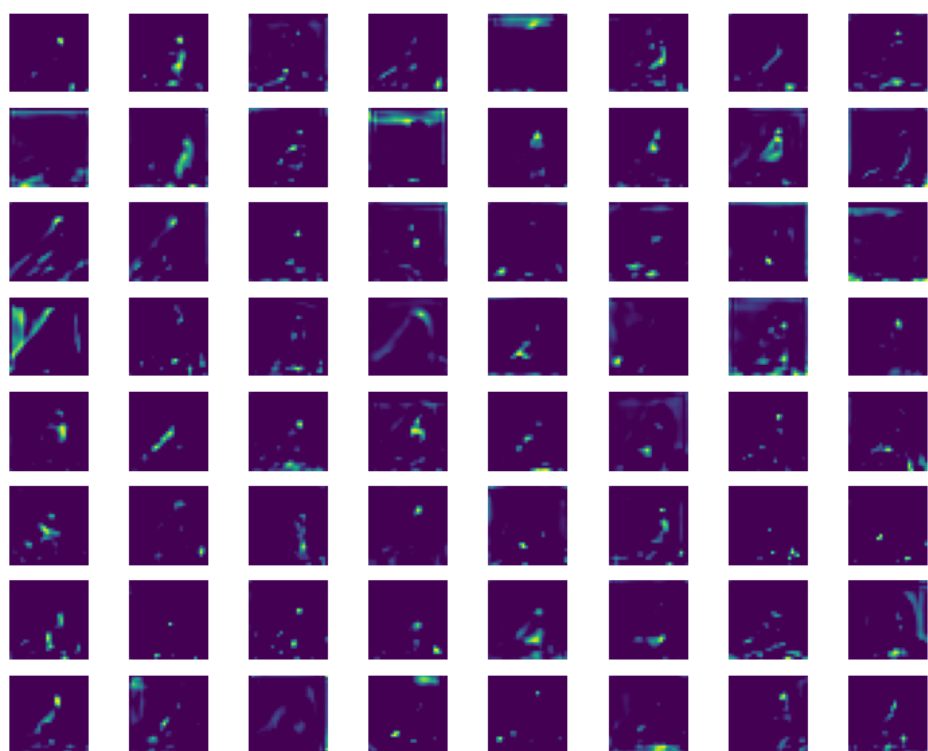
for fmap in feature_maps:
    n_maps = 64
    square = 8
    fig, axs = plt.subplots(nrows=square, ncols=square,
                             figsize=(9, 9))

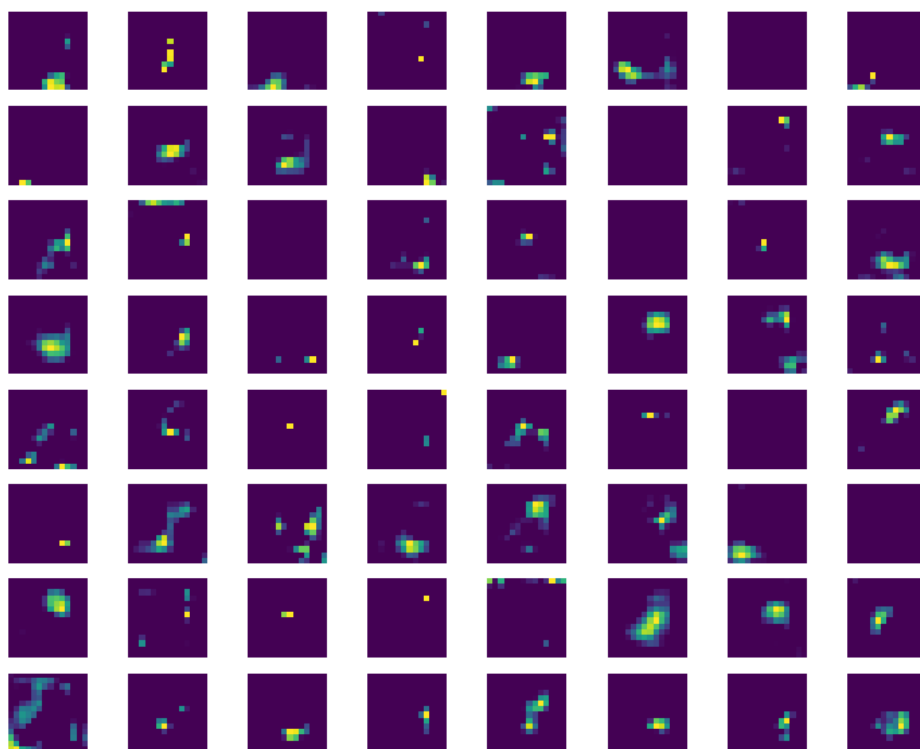
    axs = axs.flatten()
    for i in range(n_maps):
        axs[i].imshow(fmap[0, :, :, i])
        axs[i].set_axis_off()
plt.show()
```











5.5 Convoluții separabile în adâncime

Convoluțiile separabile în adâncime au fost introduse de Sifre (2014) și au fost adoptate de arhitecturi de modele populare, cum ar fi MobileNet (Howard et al., 2017) și Xception (Chollet, 2017).

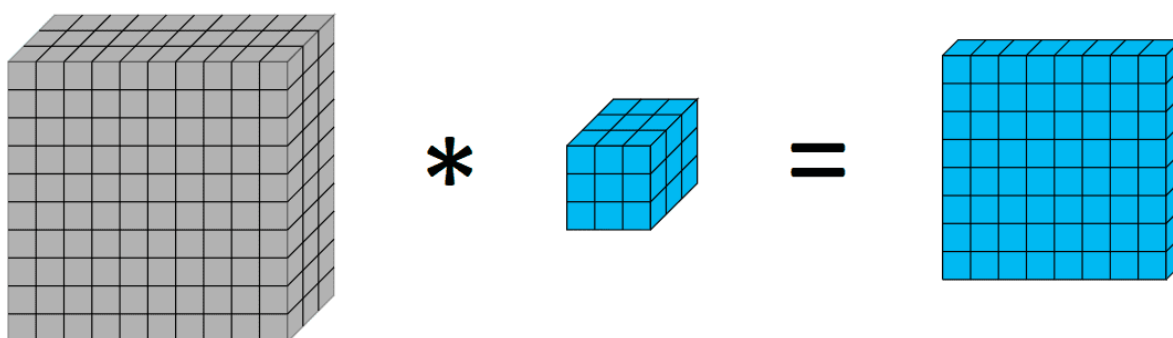


Fig. 5.3 O convoluție obișnuită (Chng, 2022)

Convoluția separabilă în adâncime este o convoluție la nivel de canal, urmată de o convoluție punctuală.

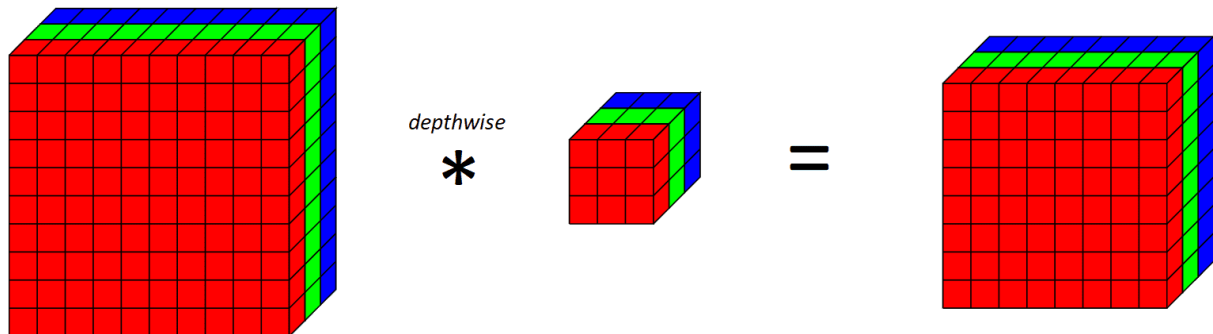


Fig. 5.4 Convoluția la nivel de canal (Chng, 2022)

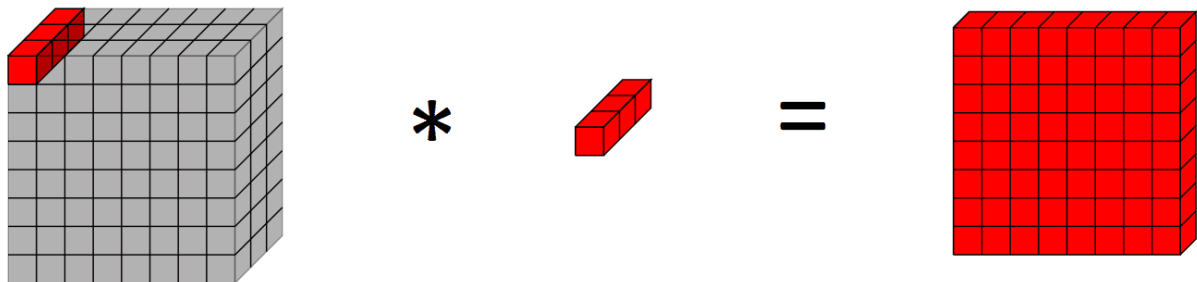


Fig. 5.5 Convoluția punctuală (Chng, 2022)

Să presupunem că dorim să aplicăm 64 de filtre convoluționale unei imagini RGB pentru a obține 64 de canale la ieșire.

Numărul de parametri în stratul convoluțional normal este $3 \times 3 \times 3 \times 64 + 64 = 1792$. Pe de altă parte, un strat convoluțional separabil în adâncime ar avea doar $(3 \times 3 \times 1 \times 3 + 3) + (1 \times 1 \times 3 \times 64 + 64) = 30 + 256 = 286$ de parametri, ceea ce reprezintă o reducere semnificativă.

Exemplu:

```
def vgg_block(layer_in, n_filters, n_conv):
    for _ in range(n_conv):
        layer_in = Conv2D(filters=n_filters, kernel_size=(3, 3),
                           padding='same', activation='relu')(layer_in)
    layer_in = MaxPooling2D(pool_size=(2, 2), strides=(2, 2))(layer_in)
    return layer_in
```



```

visible = Input(shape=(32, 32, 3))
layer = vgg_block(visible, 64, 2)
layer = vgg_block(layer, 128, 2)
layer = vgg_block(layer, 256, 2)
layer = Flatten()(layer)
layer = Dense(units=10, activation='softmax')(layer)

model = Model(inputs=visible, outputs=layer)

model.summary()

```

Model: "model_1"

Layer (type)	Output Shape	Param #
=====		
input_1 (InputLayer)	(None, 32, 32, 3)	0
conv2d_1 (Conv2D)	(None, 32, 32, 64)	1792
conv2d_2 (Conv2D)	(None, 32, 32, 64)	36928
max_pooling2d_1 (MaxPooling2D)	(None, 16, 16, 64)	0
conv2d_3 (Conv2D)	(None, 16, 16, 128)	73856
conv2d_4 (Conv2D)	(None, 16, 16, 128)	147584
max_pooling2d_2 (MaxPooling2D)	(None, 8, 8, 128)	0
conv2d_5 (Conv2D)	(None, 8, 8, 256)	295168
conv2d_6 (Conv2D)	(None, 8, 8, 256)	590080
max_pooling2d_3 (MaxPooling2D)	(None, 4, 4, 256)	0
flatten_1 (Flatten)	(None, 4096)	0
dense_1 (Dense)	(None, 10)	40970
=====		
Total params: 1,186,378		
Trainable params: 1,186,378		
Non-trainable params: 0		

```

def vgg_depthwise_block(layer_in, n_filters, n_conv):
    for _ in range(n_conv):
        layer_in = SeparableConv2D(filters=n_filters, kernel_size=(3, 3),
                                    padding='same', activation='relu')(layer_in)
    layer_in = MaxPooling2D(pool_size=(2,2), strides=(2,2))(layer_in)
    return layer_in

```

```

visible = Input(shape=(32, 32, 3))
layer = vgg_depthwise_block(visible, 64, 2)
layer = vgg_depthwise_block(layer, 128, 2)
layer = vgg_depthwise_block(layer, 256, 2)
layer = Flatten()(layer)
layer = Dense(units=10, activation='softmax')(layer)

model = Model(inputs=visible, outputs=layer)

model.summary()

```

Model: "model_2"

Layer (type)	Output Shape	Param #
=====		
input_2 (InputLayer)	(None, 32, 32, 3)	0
separable_conv2d_1 (Separabl	(None, 32, 32, 64)	283
separable_conv2d_2 (Separabl	(None, 32, 32, 64)	4736
max_pooling2d_4 (MaxPooling2	(None, 16, 16, 64)	0
separable_conv2d_3 (Separabl	(None, 16, 16, 128)	8896
separable_conv2d_4 (Separabl	(None, 16, 16, 128)	17664
max_pooling2d_5 (MaxPooling2	(None, 8, 8, 128)	0
separable_conv2d_5 (Separabl	(None, 8, 8, 256)	34176
separable_conv2d_6 (Separabl	(None, 8, 8, 256)	68096
max_pooling2d_6 (MaxPooling2	(None, 4, 4, 256)	0
flatten_2 (Flatten)	(None, 4096)	0
dense_2 (Dense)	(None, 10)	40970
=====		
Total params: 174,821		
Trainable params: 174,821		
Non-trainable params: 0		