

# Counting corners in polygons with a Convolutional Neural Network

In this notebook, I design a CNN network to count the corners of polygons in images from an archive. Images are found in the same working directory as this notebook along with the target labels.

The number of corners ranges from 3 to 10.

```
In [1]: import numpy as np
import tensorflow as tf
import time

import numpy as np
import tensorflow as tf
import time

from tensorflow import keras
from tensorflow.keras.models import Model, Sequential
from tensorflow.keras.layers import Dense, Dropout, Flatten, Input, Activation, BatchNormalization
from tensorflow.keras.layers import Conv2D, MaxPooling2D

from tensorflow.keras.optimizers import SGD, Adam, RMSprop, Nadam
from tensorflow.keras import backend as K
from tensorflow.keras import regularizers

from sklearn.metrics import *

import matplotlib
import matplotlib.pyplot as plt

import imageio.v2 as imageio
```

Define a function to load the polygon images

```
In [2]: # functions for loading the images from the course Deep Learning, Lund university (2022)
def loadImages(folder,trgFile,n):
    def load_pics(folder,n):
        imgs = []
        for i in range(n):
            img = imageio.imread(folder+"img_{:05}.png".format(i+1))
            ch = img[:, :, 0]
            imgs.append(ch)
        return np.array(imgs)

    def load_labels(fn):
        return np.loadtxt(fn, usecols=0)

    pic = load_pics(folder+"/", n)
    ndata, width, height = pic.shape

    inp = (pic/np.float32(255)).reshape(n, width, height, 1)
    trg = load_labels(trgFile)
    trg = trg[0:n]

    return inp, trg, width, height

def loadData(nTrn, nTst):
```

```

# Load data
(trnInp, trnTrg, imgW, imgH) = loadImages("polyAll-trn", "polyAll-trn_trg.csv", nTrn)
(tstInp, tstTrg, imgW, imgH) = loadImages("polyAll-tst", "polyAll-tst_trg.csv", nTst)

if tf.keras.backend.image_data_format() == 'channels_first':
    trnInp = trnInp.reshape(trnInp.shape[0], 1, imgH, imgW)
    tstInp = tstInp.reshape(tstInp.shape[0], 1, imgH, imgW)
    input_shape = (1, imgH, imgW)
else:
    trnInp = trnInp.reshape(trnInp.shape[0], imgH, imgW, 1)
    tstInp = tstInp.reshape(tstInp.shape[0], imgH, imgW, 1)
    input_shape = (imgH, imgW, 1)

#print('trnInp shape:', trnInp.shape)
#print('tstInp shape:', tstInp.shape)

#trnTrg /= 10;
#tstTrg /= 10;

#sanna convert so that 0 means 3 and 7 means 10 etc
trnTrg -= 3;
tstTrg -= 3;

return trnInp, trnTrg, tstInp, tstTrg, input_shape

```

Load and plot some example images

```

In [3]: xplot, yplot, xplot2, yplot2, plotdata_shape = loadData(10,10)

print('Dimensions of images: ', plotdata_shape)

plt.figure(1, figsize=(15,10))
plt.imshow(xplot[:10,:,:].swapaxes(0,1).reshape(100,10*100), cmap="gray")
plt.axis("off")
#plt.savefig('example_data')
print("Targets:")
print(yplot[:10])
print('actual number of corners: ', yplot[:10]+3)

```

Dimensions of images: (100, 100, 1)

Targets:

[2. 6. 3. 7. 3. 2. 2. 3. 1. 6.]

actual number of corners: [ 5. 9. 6. 10. 6. 5. 5. 6. 4. 9.]



- Load the dataset: training data and test data
- Make images binary (optional)
- Reserve 20% of the training data for validation

```

In [4]: # Load the dataset
xtrain, ytrain, xtest, ytest, input_shape = loadData(5000,5000)

print('Shape of training data' , xtrain.shape)


# make all pixels < threshold black
threshold = 0.1
#xtrain = 1.0 * (xtrain_in > threshold)
#xtest = 1.0 * (xtest_in > threshold)

```

```
# Reserve some samples for validation
val_param = int(xtrain.shape[0]*0.2)
print('Size of validation set: ', val_param)
xval = xtrain[0:val_param]
yval = ytrain[0:val_param]
xtrain = xtrain[val_param:]
ytrain = ytrain[val_param:]
```

Shape of training data (5000, 100, 100, 1)  
Size of validation set: 1000

## CNN architecture

```
In [5]: model = Sequential([
    Conv2D(16, kernel_size = (3, 3),
           activation='relu', input_shape = input_shape, padding = 'same'),
    Conv2D(16, kernel_size = (3, 3), activation = 'relu', padding = 'same'),
    MaxPooling2D(pool_size = (2, 2)),
    Conv2D(32, kernel_size = (3, 3), activation = 'relu', padding = 'same'),
    Conv2D(32, kernel_size = (3, 3), activation = 'relu', padding = 'same'),
    MaxPooling2D(pool_size = (2, 2)),
    Conv2D(32, kernel_size = (3, 3), activation = 'relu', padding = 'same'),
    MaxPooling2D(pool_size = (2, 2)),
    Conv2D(64, kernel_size = (3, 3), activation = 'relu', padding = 'same'),
    MaxPooling2D(pool_size = (2, 2)),
    Flatten(),      #(dense layer needs a 1D input)
    Dense(128, activation='relu', kernel_regularizer = regularizers.l1_l2(0.0008, 0.008)),
    Dropout(0.5),
    Dense(8),          # 8 options output
    Activation('softmax')
])
```

Define training configuration (optimizer, loss, metrics)

```
In [6]: # the loss function, optimization function
adam = Adam(learning_rate = 0.005)
#rms = RMSprop(Learning_rate = 0.008)
model.compile(loss = 'sparse_categorical_crossentropy', optimizer = adam, metrics = ['accuracy'])
model.summary()
```

Model: "sequential"

| Layer (type)                   | Output Shape         | Param # |
|--------------------------------|----------------------|---------|
| conv2d (Conv2D)                | (None, 100, 100, 16) | 160     |
| conv2d_1 (Conv2D)              | (None, 100, 100, 16) | 2320    |
| max_pooling2d (MaxPooling2D)   | (None, 50, 50, 16)   | 0       |
| conv2d_2 (Conv2D)              | (None, 50, 50, 32)   | 4640    |
| conv2d_3 (Conv2D)              | (None, 50, 50, 32)   | 9248    |
| max_pooling2d_1 (MaxPooling2D) | (None, 25, 25, 32)   | 0       |
| conv2d_4 (Conv2D)              | (None, 25, 25, 32)   | 9248    |
| max_pooling2d_2 (MaxPooling2D) | (None, 12, 12, 32)   | 0       |
| conv2d_5 (Conv2D)              | (None, 12, 12, 64)   | 18496   |
| max_pooling2d_3 (MaxPooling2D) | (None, 6, 6, 64)     | 0       |
| flatten (Flatten)              | (None, 2304)         | 0       |
| dense (Dense)                  | (None, 128)          | 295040  |
| dropout (Dropout)              | (None, 128)          | 0       |
| dense_1 (Dense)                | (None, 8)            | 1032    |
| activation (Activation)        | (None, 8)            | 0       |
| <hr/>                          |                      |         |
| Total params: 340,184          |                      |         |
| Trainable params: 340,184      |                      |         |
| Non-trainable params: 0        |                      |         |

## Train the model

Train the model with the training data and validate with the validation data.

```
In [7]: estimator = model.fit(xtrain, ytrain,
                           epochs = 150,
                           batch_size = 200, #64,#try something ~ between 20 and 200
                           verbose = 1,
                           validation_data = (xval, yval))

estimator.history
print('Accuracy: ', estimator.history['accuracy'][-1])
print(' Validation accuracy: ', estimator.history['val_accuracy'][-1])
```

Epoch 1/150  
20/20 [=====] - 12s 524ms/step - loss: 4.2896 - accuracy: 0.1797 - val\_loss: 2.7125 - val\_accuracy: 0.1960  
Epoch 2/150  
20/20 [=====] - 9s 464ms/step - loss: 2.4891 - accuracy: 0.2323 - val\_loss: 2.2288 - val\_accuracy: 0.2750  
Epoch 3/150  
20/20 [=====] - 10s 504ms/step - loss: 2.2036 - accuracy: 0.2652 - val\_loss: 2.0853 - val\_accuracy: 0.3120  
Epoch 4/150  
20/20 [=====] - 10s 495ms/step - loss: 2.1305 - accuracy: 0.2923 - val\_loss: 2.0557 - val\_accuracy: 0.3220  
Epoch 5/150  
20/20 [=====] - 11s 530ms/step - loss: 2.0541 - accuracy: 0.3203 - val\_loss: 1.9755 - val\_accuracy: 0.3390  
Epoch 6/150  
20/20 [=====] - 10s 494ms/step - loss: 2.0072 - accuracy: 0.3460 - val\_loss: 1.9361 - val\_accuracy: 0.3740  
Epoch 7/150  
20/20 [=====] - 10s 515ms/step - loss: 1.9267 - accuracy: 0.3717 - val\_loss: 1.8803 - val\_accuracy: 0.3710  
Epoch 8/150  
20/20 [=====] - 11s 555ms/step - loss: 1.9249 - accuracy: 0.3745 - val\_loss: 1.7990 - val\_accuracy: 0.4140  
Epoch 9/150  
20/20 [=====] - 9s 468ms/step - loss: 1.8352 - accuracy: 0.3898 - val\_loss: 1.7444 - val\_accuracy: 0.4130  
Epoch 10/150  
20/20 [=====] - 10s 486ms/step - loss: 1.7870 - accuracy: 0.4160 - val\_loss: 1.6824 - val\_accuracy: 0.4670  
Epoch 11/150  
20/20 [=====] - 10s 514ms/step - loss: 1.7763 - accuracy: 0.4378 - val\_loss: 1.8572 - val\_accuracy: 0.3890  
Epoch 12/150  
20/20 [=====] - 10s 481ms/step - loss: 1.7322 - accuracy: 0.4395 - val\_loss: 1.6018 - val\_accuracy: 0.4880  
Epoch 13/150  
20/20 [=====] - 10s 497ms/step - loss: 1.6005 - accuracy: 0.4805 - val\_loss: 1.6087 - val\_accuracy: 0.4510  
Epoch 14/150  
20/20 [=====] - 9s 467ms/step - loss: 1.5664 - accuracy: 0.5052 - val\_loss: 1.5710 - val\_accuracy: 0.5010  
Epoch 15/150  
20/20 [=====] - 10s 496ms/step - loss: 1.5830 - accuracy: 0.5048 - val\_loss: 1.6474 - val\_accuracy: 0.4420  
Epoch 16/150  
20/20 [=====] - 10s 499ms/step - loss: 1.5639 - accuracy: 0.5052 - val\_loss: 1.5754 - val\_accuracy: 0.4800  
Epoch 17/150  
20/20 [=====] - 12s 593ms/step - loss: 1.5183 - accuracy: 0.5132 - val\_loss: 1.4635 - val\_accuracy: 0.5290  
Epoch 18/150  
20/20 [=====] - 11s 536ms/step - loss: 1.4136 - accuracy: 0.5433 - val\_loss: 1.4640 - val\_accuracy: 0.5100  
Epoch 19/150  
20/20 [=====] - 15s 753ms/step - loss: 1.5533 - accuracy: 0.5048 - val\_loss: 1.5047 - val\_accuracy: 0.5240  
Epoch 20/150  
20/20 [=====] - 15s 748ms/step - loss: 1.4560 - accuracy: 0.5405 - val\_loss: 1.3970 - val\_accuracy: 0.5860  
Epoch 21/150  
20/20 [=====] - 13s 677ms/step - loss: 1.3766 - accuracy: 0.5727 - val\_loss: 1.3075 - val\_accuracy: 0.6220  
Epoch 22/150  
20/20 [=====] - 13s 631ms/step - loss: 1.3736 - accuracy: 0.5665 - val\_loss: 1.3111 - val\_accuracy: 0.6160

Epoch 23/150  
20/20 [=====] - 14s 698ms/step - loss: 1.3752 - accuracy: 0.5665 - val\_loss: 1.4385 - val\_accuracy: 0.5380  
Epoch 24/150  
20/20 [=====] - 13s 641ms/step - loss: 1.3310 - accuracy: 0.6077 - val\_loss: 1.3139 - val\_accuracy: 0.6010  
Epoch 25/150  
20/20 [=====] - 14s 704ms/step - loss: 1.2875 - accuracy: 0.6097 - val\_loss: 1.2933 - val\_accuracy: 0.6100  
Epoch 26/150  
20/20 [=====] - 14s 691ms/step - loss: 1.3610 - accuracy: 0.5890 - val\_loss: 1.5162 - val\_accuracy: 0.5220  
Epoch 27/150  
20/20 [=====] - 14s 682ms/step - loss: 1.3589 - accuracy: 0.5817 - val\_loss: 1.3322 - val\_accuracy: 0.5860  
Epoch 28/150  
20/20 [=====] - 14s 688ms/step - loss: 1.3326 - accuracy: 0.5925 - val\_loss: 1.3414 - val\_accuracy: 0.6080  
Epoch 29/150  
20/20 [=====] - 14s 682ms/step - loss: 1.2210 - accuracy: 0.6430 - val\_loss: 1.2274 - val\_accuracy: 0.6280  
Epoch 30/150  
20/20 [=====] - 13s 639ms/step - loss: 1.1818 - accuracy: 0.6660 - val\_loss: 1.2396 - val\_accuracy: 0.6460  
Epoch 31/150  
20/20 [=====] - 13s 650ms/step - loss: 1.2140 - accuracy: 0.6528 - val\_loss: 1.2523 - val\_accuracy: 0.6360  
Epoch 32/150  
20/20 [=====] - 14s 694ms/step - loss: 1.2407 - accuracy: 0.6492 - val\_loss: 1.2530 - val\_accuracy: 0.6590  
Epoch 33/150  
20/20 [=====] - 13s 635ms/step - loss: 1.2600 - accuracy: 0.6430 - val\_loss: 1.3414 - val\_accuracy: 0.5870  
Epoch 34/150  
20/20 [=====] - 14s 674ms/step - loss: 1.2850 - accuracy: 0.6237 - val\_loss: 1.2364 - val\_accuracy: 0.6420  
Epoch 35/150  
20/20 [=====] - 14s 683ms/step - loss: 1.1863 - accuracy: 0.6708 - val\_loss: 1.2886 - val\_accuracy: 0.6470  
Epoch 36/150  
20/20 [=====] - 13s 647ms/step - loss: 1.2820 - accuracy: 0.6425 - val\_loss: 1.3435 - val\_accuracy: 0.6010  
Epoch 37/150  
20/20 [=====] - 14s 715ms/step - loss: 1.2336 - accuracy: 0.6530 - val\_loss: 1.1823 - val\_accuracy: 0.6830  
Epoch 38/150  
20/20 [=====] - 12s 608ms/step - loss: 1.1292 - accuracy: 0.6990 - val\_loss: 1.1676 - val\_accuracy: 0.6840  
Epoch 39/150  
20/20 [=====] - 12s 616ms/step - loss: 1.1727 - accuracy: 0.6737 - val\_loss: 1.3240 - val\_accuracy: 0.5770  
Epoch 40/150  
20/20 [=====] - 14s 698ms/step - loss: 1.1519 - accuracy: 0.6823 - val\_loss: 1.2586 - val\_accuracy: 0.6400  
Epoch 41/150  
20/20 [=====] - 12s 600ms/step - loss: 1.1588 - accuracy: 0.6888 - val\_loss: 1.4547 - val\_accuracy: 0.5770  
Epoch 42/150  
20/20 [=====] - 14s 688ms/step - loss: 1.2182 - accuracy: 0.6690 - val\_loss: 1.2891 - val\_accuracy: 0.6630  
Epoch 43/150  
20/20 [=====] - 13s 634ms/step - loss: 1.1986 - accuracy: 0.6708 - val\_loss: 1.2363 - val\_accuracy: 0.6410  
Epoch 44/150  
20/20 [=====] - 14s 725ms/step - loss: 1.1080 - accuracy: 0.7010 - val\_loss: 1.2077 - val\_accuracy: 0.6600

Epoch 45/150  
20/20 [=====] - 14s 693ms/step - loss: 1.3762 - accuracy: 0.5853 - val\_loss: 1.4872 - val\_accuracy: 0.5690  
Epoch 46/150  
20/20 [=====] - 14s 687ms/step - loss: 1.1783 - accuracy: 0.6620 - val\_loss: 1.2871 - val\_accuracy: 0.6370  
Epoch 47/150  
20/20 [=====] - 14s 707ms/step - loss: 1.1140 - accuracy: 0.6985 - val\_loss: 1.1693 - val\_accuracy: 0.6810  
Epoch 48/150  
20/20 [=====] - 14s 685ms/step - loss: 1.0412 - accuracy: 0.7347 - val\_loss: 1.1881 - val\_accuracy: 0.6510  
Epoch 49/150  
20/20 [=====] - 12s 597ms/step - loss: 1.0650 - accuracy: 0.7255 - val\_loss: 1.2110 - val\_accuracy: 0.6420  
Epoch 50/150  
20/20 [=====] - 13s 642ms/step - loss: 1.0904 - accuracy: 0.7128 - val\_loss: 1.2332 - val\_accuracy: 0.6640  
Epoch 51/150  
20/20 [=====] - 14s 702ms/step - loss: 1.0972 - accuracy: 0.7145 - val\_loss: 1.2256 - val\_accuracy: 0.6800  
Epoch 52/150  
20/20 [=====] - 13s 660ms/step - loss: 1.0889 - accuracy: 0.7207 - val\_loss: 1.1858 - val\_accuracy: 0.6580  
Epoch 53/150  
20/20 [=====] - 13s 669ms/step - loss: 1.0177 - accuracy: 0.7625 - val\_loss: 1.1815 - val\_accuracy: 0.6860  
Epoch 54/150  
20/20 [=====] - 13s 648ms/step - loss: 1.0216 - accuracy: 0.7508 - val\_loss: 1.1778 - val\_accuracy: 0.7020  
Epoch 55/150  
20/20 [=====] - 14s 685ms/step - loss: 1.1017 - accuracy: 0.7180 - val\_loss: 1.3078 - val\_accuracy: 0.6440  
Epoch 56/150  
20/20 [=====] - 14s 719ms/step - loss: 1.0684 - accuracy: 0.7303 - val\_loss: 1.2314 - val\_accuracy: 0.6560  
Epoch 57/150  
20/20 [=====] - 13s 647ms/step - loss: 1.0451 - accuracy: 0.7448 - val\_loss: 1.2947 - val\_accuracy: 0.6630  
Epoch 58/150  
20/20 [=====] - 14s 688ms/step - loss: 1.0529 - accuracy: 0.7380 - val\_loss: 1.2028 - val\_accuracy: 0.6610  
Epoch 59/150  
20/20 [=====] - 14s 718ms/step - loss: 1.0592 - accuracy: 0.7362 - val\_loss: 1.1584 - val\_accuracy: 0.6890  
Epoch 60/150  
20/20 [=====] - 13s 649ms/step - loss: 1.0184 - accuracy: 0.7605 - val\_loss: 1.2021 - val\_accuracy: 0.6540  
Epoch 61/150  
20/20 [=====] - 14s 713ms/step - loss: 1.0523 - accuracy: 0.7475 - val\_loss: 1.4782 - val\_accuracy: 0.6280  
Epoch 62/150  
20/20 [=====] - 14s 696ms/step - loss: 1.1011 - accuracy: 0.7253 - val\_loss: 1.2089 - val\_accuracy: 0.6750  
Epoch 63/150  
20/20 [=====] - 13s 645ms/step - loss: 1.1261 - accuracy: 0.7105 - val\_loss: 1.2732 - val\_accuracy: 0.6450  
Epoch 64/150  
20/20 [=====] - 14s 678ms/step - loss: 1.0618 - accuracy: 0.7383 - val\_loss: 1.2609 - val\_accuracy: 0.6540  
Epoch 65/150  
20/20 [=====] - 13s 663ms/step - loss: 1.0868 - accuracy: 0.7278 - val\_loss: 1.2836 - val\_accuracy: 0.6120  
Epoch 66/150  
20/20 [=====] - 12s 610ms/step - loss: 1.0289 - accuracy: 0.7550 - val\_loss: 1.1852 - val\_accuracy: 0.6960

Epoch 67/150  
20/20 [=====] - 12s 602ms/step - loss: 0.9764 - accuracy: 0.7830 - val\_loss: 1.2776 - val\_accuracy: 0.6830  
Epoch 68/150  
20/20 [=====] - 13s 668ms/step - loss: 0.9988 - accuracy: 0.7740 - val\_loss: 1.2244 - val\_accuracy: 0.6850  
Epoch 69/150  
20/20 [=====] - 13s 670ms/step - loss: 1.0188 - accuracy: 0.7598 - val\_loss: 1.1966 - val\_accuracy: 0.6860  
Epoch 70/150  
20/20 [=====] - 13s 649ms/step - loss: 1.0866 - accuracy: 0.7345 - val\_loss: 1.1885 - val\_accuracy: 0.6930  
Epoch 71/150  
20/20 [=====] - 14s 690ms/step - loss: 1.0806 - accuracy: 0.7370 - val\_loss: 1.2118 - val\_accuracy: 0.6980  
Epoch 72/150  
20/20 [=====] - 13s 624ms/step - loss: 0.9671 - accuracy: 0.7870 - val\_loss: 1.2062 - val\_accuracy: 0.7050  
Epoch 73/150  
20/20 [=====] - 14s 697ms/step - loss: 0.9662 - accuracy: 0.7797 - val\_loss: 1.3164 - val\_accuracy: 0.6600  
Epoch 74/150  
20/20 [=====] - 14s 697ms/step - loss: 1.1073 - accuracy: 0.7107 - val\_loss: 1.2128 - val\_accuracy: 0.6870  
Epoch 75/150  
20/20 [=====] - 13s 630ms/step - loss: 1.0110 - accuracy: 0.7638 - val\_loss: 1.2464 - val\_accuracy: 0.6490  
Epoch 76/150  
20/20 [=====] - 12s 607ms/step - loss: 0.9918 - accuracy: 0.7765 - val\_loss: 1.2067 - val\_accuracy: 0.6990  
Epoch 77/150  
20/20 [=====] - 13s 654ms/step - loss: 0.9622 - accuracy: 0.7875 - val\_loss: 1.2466 - val\_accuracy: 0.6900  
Epoch 78/150  
20/20 [=====] - 15s 752ms/step - loss: 0.9441 - accuracy: 0.8000 - val\_loss: 1.2608 - val\_accuracy: 0.6550  
Epoch 79/150  
20/20 [=====] - 14s 672ms/step - loss: 0.9955 - accuracy: 0.7825 - val\_loss: 1.2582 - val\_accuracy: 0.6560  
Epoch 80/150  
20/20 [=====] - 13s 655ms/step - loss: 1.0105 - accuracy: 0.7592 - val\_loss: 1.2382 - val\_accuracy: 0.6620  
Epoch 81/150  
20/20 [=====] - 13s 653ms/step - loss: 1.0082 - accuracy: 0.7722 - val\_loss: 1.4523 - val\_accuracy: 0.5950  
Epoch 82/150  
20/20 [=====] - 13s 635ms/step - loss: 1.1743 - accuracy: 0.6820 - val\_loss: 1.3513 - val\_accuracy: 0.6770  
Epoch 83/150  
20/20 [=====] - 14s 697ms/step - loss: 1.0107 - accuracy: 0.7768 - val\_loss: 1.2750 - val\_accuracy: 0.6930  
Epoch 84/150  
20/20 [=====] - 12s 620ms/step - loss: 0.9545 - accuracy: 0.8008 - val\_loss: 1.2327 - val\_accuracy: 0.6780  
Epoch 85/150  
20/20 [=====] - 13s 657ms/step - loss: 0.9460 - accuracy: 0.8033 - val\_loss: 1.2060 - val\_accuracy: 0.7100  
Epoch 86/150  
20/20 [=====] - 13s 671ms/step - loss: 0.9808 - accuracy: 0.7860 - val\_loss: 1.3297 - val\_accuracy: 0.6640  
Epoch 87/150  
20/20 [=====] - 13s 646ms/step - loss: 0.9792 - accuracy: 0.7785 - val\_loss: 1.2415 - val\_accuracy: 0.6820  
Epoch 88/150  
20/20 [=====] - 14s 696ms/step - loss: 0.9716 - accuracy: 0.7885 - val\_loss: 1.2299 - val\_accuracy: 0.7100

Epoch 89/150  
20/20 [=====] - 13s 675ms/step - loss: 0.9462 - accuracy: 0.7928 - val\_loss: 1.1691 - val\_accuracy: 0.6920  
Epoch 90/150  
20/20 [=====] - 12s 612ms/step - loss: 0.9735 - accuracy: 0.7805 - val\_loss: 1.3134 - val\_accuracy: 0.6390  
Epoch 91/150  
20/20 [=====] - 14s 685ms/step - loss: 0.9154 - accuracy: 0.8073 - val\_loss: 1.2417 - val\_accuracy: 0.6740  
Epoch 92/150  
20/20 [=====] - 14s 689ms/step - loss: 0.9443 - accuracy: 0.7960 - val\_loss: 1.2967 - val\_accuracy: 0.6920  
Epoch 93/150  
20/20 [=====] - 13s 625ms/step - loss: 0.9246 - accuracy: 0.8102 - val\_loss: 1.3675 - val\_accuracy: 0.6360  
Epoch 94/150  
20/20 [=====] - 14s 675ms/step - loss: 0.9682 - accuracy: 0.7900 - val\_loss: 1.3426 - val\_accuracy: 0.6860  
Epoch 95/150  
20/20 [=====] - 14s 694ms/step - loss: 0.9788 - accuracy: 0.7860 - val\_loss: 1.2124 - val\_accuracy: 0.7040  
Epoch 96/150  
20/20 [=====] - 14s 702ms/step - loss: 0.8940 - accuracy: 0.8213 - val\_loss: 1.3049 - val\_accuracy: 0.6950  
Epoch 97/150  
20/20 [=====] - 13s 653ms/step - loss: 0.9439 - accuracy: 0.8050 - val\_loss: 1.3230 - val\_accuracy: 0.6780  
Epoch 98/150  
20/20 [=====] - 13s 639ms/step - loss: 0.9535 - accuracy: 0.8073 - val\_loss: 1.4205 - val\_accuracy: 0.6810  
Epoch 99/150  
20/20 [=====] - 14s 688ms/step - loss: 1.0760 - accuracy: 0.7542 - val\_loss: 1.2428 - val\_accuracy: 0.6990  
Epoch 100/150  
20/20 [=====] - 13s 668ms/step - loss: 0.9451 - accuracy: 0.8127 - val\_loss: 1.2182 - val\_accuracy: 0.7200  
Epoch 101/150  
20/20 [=====] - 13s 637ms/step - loss: 0.9302 - accuracy: 0.8075 - val\_loss: 1.2816 - val\_accuracy: 0.7150  
Epoch 102/150  
20/20 [=====] - 13s 673ms/step - loss: 0.9076 - accuracy: 0.8207 - val\_loss: 1.1971 - val\_accuracy: 0.7090  
Epoch 103/150  
20/20 [=====] - 13s 644ms/step - loss: 0.8582 - accuracy: 0.8397 - val\_loss: 1.2660 - val\_accuracy: 0.6840  
Epoch 104/150  
20/20 [=====] - 13s 648ms/step - loss: 0.9588 - accuracy: 0.7962 - val\_loss: 1.3870 - val\_accuracy: 0.6900  
Epoch 105/150  
20/20 [=====] - 12s 608ms/step - loss: 0.9555 - accuracy: 0.8060 - val\_loss: 1.3157 - val\_accuracy: 0.7160  
Epoch 106/150  
20/20 [=====] - 13s 649ms/step - loss: 0.9029 - accuracy: 0.8242 - val\_loss: 1.3012 - val\_accuracy: 0.7040  
Epoch 107/150  
20/20 [=====] - 13s 634ms/step - loss: 0.8752 - accuracy: 0.8317 - val\_loss: 1.2157 - val\_accuracy: 0.7080  
Epoch 108/150  
20/20 [=====] - 13s 673ms/step - loss: 0.8747 - accuracy: 0.8267 - val\_loss: 1.2019 - val\_accuracy: 0.7020  
Epoch 109/150  
20/20 [=====] - 14s 704ms/step - loss: 0.8981 - accuracy: 0.8215 - val\_loss: 1.2254 - val\_accuracy: 0.7040  
Epoch 110/150  
20/20 [=====] - 13s 666ms/step - loss: 0.9238 - accuracy: 0.8175 - val\_loss: 1.1893 - val\_accuracy: 0.7230

Epoch 111/150  
20/20 [=====] - 14s 713ms/step - loss: 0.9616 - accuracy: 0.7922 - val\_loss: 1.3167 - val\_accuracy: 0.6740  
Epoch 112/150  
20/20 [=====] - 14s 686ms/step - loss: 0.9351 - accuracy: 0.8145 - val\_loss: 1.3253 - val\_accuracy: 0.6670  
Epoch 113/150  
20/20 [=====] - 14s 687ms/step - loss: 0.9282 - accuracy: 0.8180 - val\_loss: 1.4493 - val\_accuracy: 0.6870  
Epoch 114/150  
20/20 [=====] - 14s 703ms/step - loss: 0.9599 - accuracy: 0.7993 - val\_loss: 1.2799 - val\_accuracy: 0.6840  
Epoch 115/150  
20/20 [=====] - 12s 608ms/step - loss: 0.8968 - accuracy: 0.8290 - val\_loss: 1.8162 - val\_accuracy: 0.5560  
Epoch 116/150  
20/20 [=====] - 13s 651ms/step - loss: 1.1539 - accuracy: 0.7153 - val\_loss: 1.6060 - val\_accuracy: 0.5920  
Epoch 117/150  
20/20 [=====] - 13s 636ms/step - loss: 1.0708 - accuracy: 0.7525 - val\_loss: 1.2723 - val\_accuracy: 0.7050  
Epoch 118/150  
20/20 [=====] - 12s 622ms/step - loss: 0.9551 - accuracy: 0.7995 - val\_loss: 1.2877 - val\_accuracy: 0.6940  
Epoch 119/150  
20/20 [=====] - 12s 612ms/step - loss: 0.8928 - accuracy: 0.8260 - val\_loss: 1.2620 - val\_accuracy: 0.6950  
Epoch 120/150  
20/20 [=====] - 13s 643ms/step - loss: 0.8420 - accuracy: 0.8440 - val\_loss: 1.2819 - val\_accuracy: 0.7120  
Epoch 121/150  
20/20 [=====] - 12s 616ms/step - loss: 0.8686 - accuracy: 0.8418 - val\_loss: 1.6686 - val\_accuracy: 0.6480  
Epoch 122/150  
20/20 [=====] - 13s 663ms/step - loss: 0.9680 - accuracy: 0.7950 - val\_loss: 1.1815 - val\_accuracy: 0.7210  
Epoch 123/150  
20/20 [=====] - 14s 683ms/step - loss: 0.9133 - accuracy: 0.8190 - val\_loss: 1.3029 - val\_accuracy: 0.7070  
Epoch 124/150  
20/20 [=====] - 14s 690ms/step - loss: 0.8465 - accuracy: 0.8410 - val\_loss: 1.3585 - val\_accuracy: 0.7020  
Epoch 125/150  
20/20 [=====] - 13s 629ms/step - loss: 0.8939 - accuracy: 0.8220 - val\_loss: 1.2992 - val\_accuracy: 0.6940  
Epoch 126/150  
20/20 [=====] - 14s 677ms/step - loss: 0.8812 - accuracy: 0.8263 - val\_loss: 1.2512 - val\_accuracy: 0.6990  
Epoch 127/150  
20/20 [=====] - 13s 657ms/step - loss: 0.8717 - accuracy: 0.8332 - val\_loss: 1.3638 - val\_accuracy: 0.6630  
Epoch 128/150  
20/20 [=====] - 13s 619ms/step - loss: 0.8809 - accuracy: 0.8342 - val\_loss: 1.2938 - val\_accuracy: 0.7270  
Epoch 129/150  
20/20 [=====] - 13s 662ms/step - loss: 0.8715 - accuracy: 0.8372 - val\_loss: 1.3591 - val\_accuracy: 0.6680  
Epoch 130/150  
20/20 [=====] - 14s 701ms/step - loss: 0.9130 - accuracy: 0.8158 - val\_loss: 1.4229 - val\_accuracy: 0.6580  
Epoch 131/150  
20/20 [=====] - 14s 698ms/step - loss: 1.0063 - accuracy: 0.7793 - val\_loss: 1.5037 - val\_accuracy: 0.5930  
Epoch 132/150  
20/20 [=====] - 14s 685ms/step - loss: 0.9566 - accuracy: 0.8040 - val\_loss: 1.2440 - val\_accuracy: 0.7100

```
Epoch 133/150
20/20 [=====] - 13s 652ms/step - loss: 0.9282 - accuracy: 0.8120 - val_loss: 1.1941 - val_accuracy: 0.7140
Epoch 134/150
20/20 [=====] - 14s 679ms/step - loss: 0.8972 - accuracy: 0.8240 - val_loss: 1.2523 - val_accuracy: 0.6920
Epoch 135/150
20/20 [=====] - 14s 675ms/step - loss: 0.9847 - accuracy: 0.7845 - val_loss: 1.2782 - val_accuracy: 0.6750
Epoch 136/150
20/20 [=====] - 10s 506ms/step - loss: 0.9474 - accuracy: 0.8002 - val_loss: 1.5418 - val_accuracy: 0.6530
Epoch 137/150
20/20 [=====] - 10s 510ms/step - loss: 0.9174 - accuracy: 0.8175 - val_loss: 1.2390 - val_accuracy: 0.6990
Epoch 138/150
20/20 [=====] - 13s 644ms/step - loss: 0.9188 - accuracy: 0.8085 - val_loss: 1.4276 - val_accuracy: 0.6800
Epoch 139/150
20/20 [=====] - 11s 554ms/step - loss: 0.9391 - accuracy: 0.8015 - val_loss: 1.3604 - val_accuracy: 0.6710
Epoch 140/150
20/20 [=====] - 10s 496ms/step - loss: 0.9729 - accuracy: 0.7853 - val_loss: 1.3378 - val_accuracy: 0.6430
Epoch 141/150
20/20 [=====] - 11s 532ms/step - loss: 0.8672 - accuracy: 0.8330 - val_loss: 1.3197 - val_accuracy: 0.7020
Epoch 142/150
20/20 [=====] - 10s 484ms/step - loss: 0.8242 - accuracy: 0.8612 - val_loss: 1.3184 - val_accuracy: 0.6890
Epoch 143/150
20/20 [=====] - 10s 517ms/step - loss: 0.8760 - accuracy: 0.8250 - val_loss: 1.1989 - val_accuracy: 0.7230
Epoch 144/150
20/20 [=====] - 10s 492ms/step - loss: 0.8683 - accuracy: 0.8320 - val_loss: 1.3153 - val_accuracy: 0.7060
Epoch 145/150
20/20 [=====] - 10s 516ms/step - loss: 0.8242 - accuracy: 0.8540 - val_loss: 1.2756 - val_accuracy: 0.7120
Epoch 146/150
20/20 [=====] - 10s 511ms/step - loss: 0.8015 - accuracy: 0.8658 - val_loss: 1.3503 - val_accuracy: 0.6850
Epoch 147/150
20/20 [=====] - 10s 512ms/step - loss: 0.9056 - accuracy: 0.8160 - val_loss: 1.2880 - val_accuracy: 0.6740
Epoch 148/150
20/20 [=====] - 9s 478ms/step - loss: 0.9892 - accuracy: 0.7810 - val_loss: 1.2629 - val_accuracy: 0.6710
Epoch 149/150
20/20 [=====] - 10s 525ms/step - loss: 0.9194 - accuracy: 0.8130 - val_loss: 1.3253 - val_accuracy: 0.6880
Epoch 150/150
20/20 [=====] - 10s 487ms/step - loss: 0.8555 - accuracy: 0.8495 - val_loss: 1.3136 - val_accuracy: 0.6960
Accuracy: 0.8495000004768372
Validation accuracy: 0.6959999799728394
```

Training and validation plots

```
In [8]: plt.figure(1, figsize = (9,6))
plt.subplot(121)
# Plot the training error
plt.plot(estimator.history['loss'], label = 'Training')
plt.plot(estimator.history['val_loss'], label = 'Validation')
plt.ylabel('Error')
```

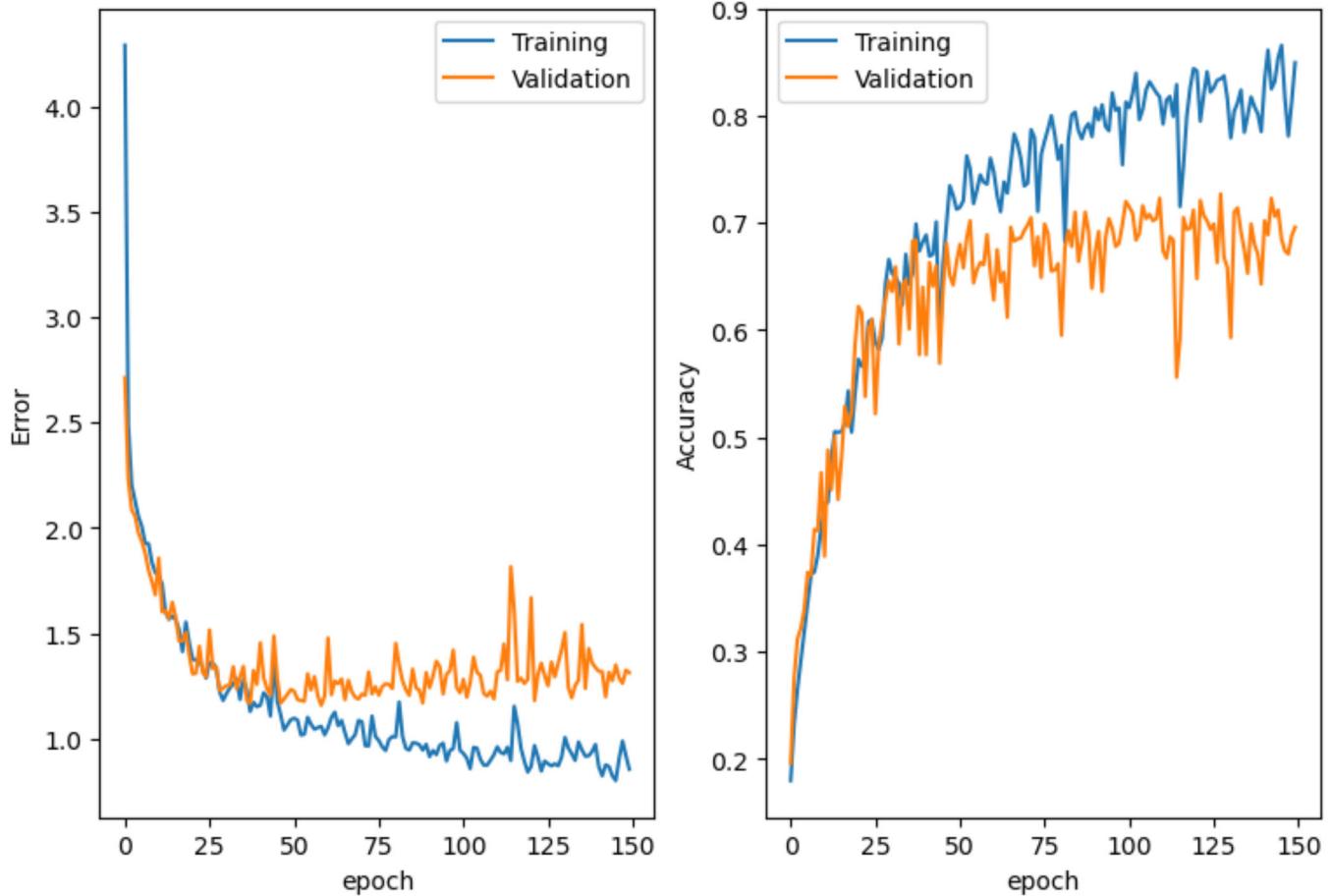
```

plt.xlabel('epoch')
plt.legend()
# plt.show()

# Plot the accuracy
plt.subplot(122)
plt.plot(estimator.history['accuracy'], label = 'Training')
plt.plot(estimator.history['val_accuracy'], label = 'Validation')
plt.ylabel('Accuracy')
plt.xlabel('epoch')
plt.legend()

```

Out[8]: <matplotlib.legend.Legend at 0x1a68907b1f0>



## Evaluate

Time to evaluate the model with the test data

```

In [10]: print('Evaluating model: ')
scores = model.evaluate(xtest, ytest, batch_size = 128) #prints out score.
print("test loss, test acc:", round(scores[0], 4), round(scores[1], 4))

```

Evaluating model:  
40/40 [=====] - 3s 75ms/step - loss: 1.3130 - accuracy: 0.7074  
test loss, test acc: 1.313 0.7074

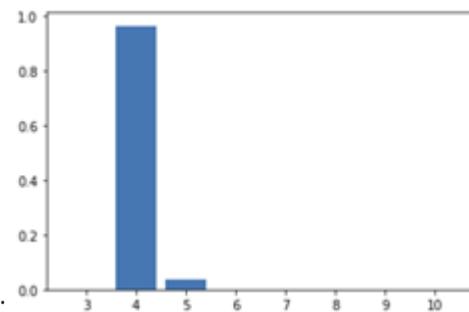
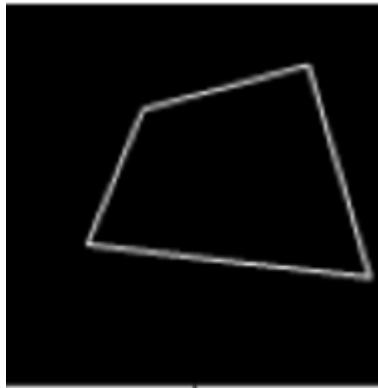
## Results summary

- Around 70% polygons were correctly classified
- Model is slightly overtrained

# What went wrong? Examples of correct and wrongly classified polygons

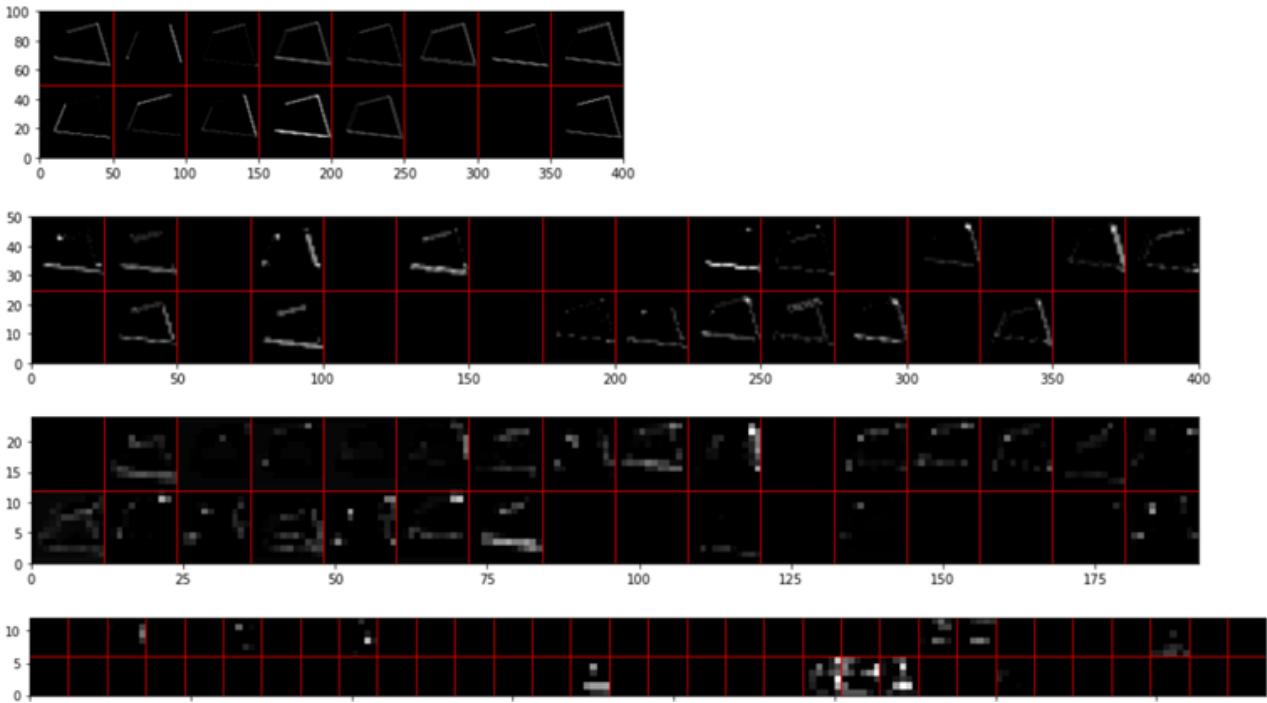
- Showing typical example of polygons that were harder to identify
- Display the filters

Starting with a correctly classified polygon:



predicted as 4 corners:

the filters convoluted with this polygon look like this:

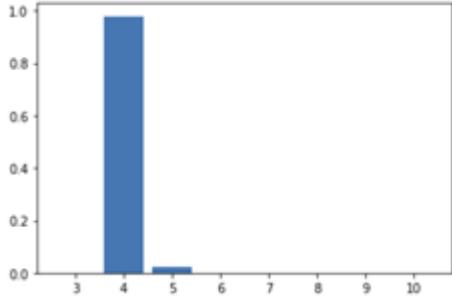


- Note how the edges are identified in the earlier convolutional filters

and an example of a wrongly classified polygon:



classified as:



Note that:

- one of the corners are close to 180 degrees which is most probably the corner that is not counted
- there is an existing, but lower, probability for 5 corners

## Statistics

