

Counting corners in polygons. Dataset 1

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Outline

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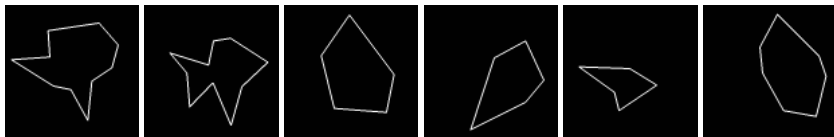
Examples of wrong predictions

Conclusion

Description of the dataset

- ▶ Images of polygons with 3 to 10 sides.
- ▶ Images have 100x100x1 size. 100x100 pixel and 1 is represents the colour of the pixel (white or black)
- ▶ Training dataset: 5000 images. Test dataset: 5000 images.

Example of dataset



Pre-processing of data

- ▶ Import library: `from tensorflow.keras.utils import to_categorical`
- ▶ `trg = to_categorical(trg[0:n]-3)`
- ▶ One hot encoding: `to_categorical` converts integers into binary class matrix: it prepares the labels for the categorical cross-entropy. The labels are d_1, d_2, \dots, d_8 , where the label is $d_1 = (1, 0, 0, 0, 0, 0, 0)$, $d_2 = (1, 0, 0, 0, 0, 0, 0)$, \dots , $d_8 = (0, 0, 0, 0, 0, 0, 1)$.

Choice of the model

- ▶ Since we are dealing with images we use a **Convolutional Neural Network** (CNN).
- ▶ **Two convolutional layers:** one to detect lines and one to detect corners.
- ▶ The **kernel** of the convolutional layers must have size comparable to the thickness of lines in terms of pixels (Guess: 5x5).
- ▶ **Zero padding** in order not to decrease the size of the image after the convolution.
- ▶ Small number of **hidden layers** in the MLP and non linear activation function in the hidden layers (RELU)
- ▶ **Output activation function:** softmax. It gives to probability of being in each class.
- ▶ Number of **output nodes** equal the numbers of classes: 8.
- ▶ **Loss function:** categorical cross entropy since we are dealing with classification problems.
- ▶ **Optimizer:** ADAM to keep the past gradient on the count for a faster optimization process.

CNN architecture

```
# Define the CNN model
model = Sequential([
    Conv2D(60, kernel_size=(6, 6), padding='same', activation='relu',
          input_shape=input_shape),
    MaxPooling2D(pool_size=(5, 5)),
    Conv2D(60, kernel_size=(5, 5), padding='same', activation='relu'),
    MaxPooling2D(pool_size=(4, 4)),
    Flatten(),
    Dropout(0.3),
    Dense(15, activation='relu'),
    Dense(8),
    Activation('softmax')
])
```

Layer (type)	Output Shape	Param #
conv2d_8 (Conv2D)	(None, 100, 100, 60)	2220
max_pooling2d_8 (MaxPooling2D)	(None, 20, 20, 60)	0
conv2d_9 (Conv2D)	(None, 20, 20, 60)	90060
max_pooling2d_9 (MaxPooling2D)	(None, 5, 5, 60)	0
flatten_4 (Flatten)	(None, 1500)	0
dropout_4 (Dropout)	(None, 1500)	0
dense_8 (Dense)	(None, 15)	22515
dense_9 (Dense)	(None, 8)	128
activation_4 (Activation)	(None, 8)	0
Total params: 114,923		
Trainable params: 114,923		
Non-trainable params: 0		

MLP architecture

Hyperparameters:

- ▶ Learning rate = 0.005
- ▶ Dropout = 0.3
- ▶ Epochs = 30
- ▶ Batch size = 80

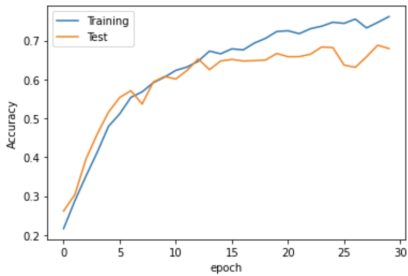
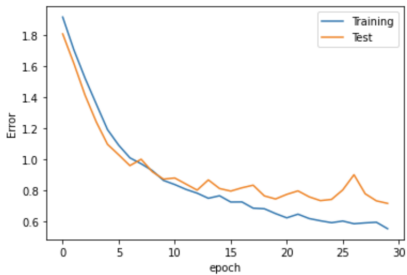
```
adam = Adam(learning_rate=0.005)
model.compile(loss='categorical_crossentropy',
              optimizer=adam, metrics=['accuracy'])
model.summary()

# Now train the model
estimator = model.fit(trnInp, trnTrg,
                      epochs=30,
                      batch_size=80,
                      verbose=0,
                      validation_data=(tstInp, tstTrg),
                      callbacks=[CustomCallback()])
```

Results

Accuracy and Loss function

- ▶ Train error function: 0.6
- ▶ Test error function: 0.8
- ▶ Train accuracy: 0.73
- ▶ Test accuracy: 0.65



Examples of wrong predictions



Figure: True: 8. Predicted:9

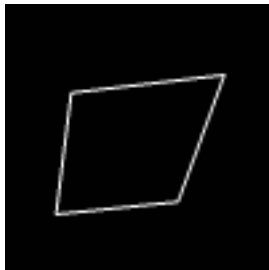


Figure: True: 4. Predicted:5



Figure: True: 6. Predicted:5

Conclusion

Results:

- ▶ Best results obtained with only two convolutional blocks.
- ▶ Bigger size of the kernels in the CNN.
- ▶ Bigger size of the pooling (downsampling) to improve efficiency.
- ▶ Dropout on the input layer works better than in the hidden layers.

Possible improvements:

- ▶ Adding more filters and more hidden layers in the CNN
- ▶ Decreasing batch-size
- ▶ Increase the number of data (augmentation) by flipping or rotating images (any $SO(n)$ matrix).