

# Codes and Mathematical Expressions

## Codes:

```
DATA_DIR = ".../input/data-zel-d2-17-3/data_özel_D2_17_3"  
TRAINING_DIR = DATA_DIR + "/train"  
VALIDATION_DIR = DATA_DIR + "/val"  
TEST_DIR = DATA_DIR + "/test"
```

```
BATCH_SIZE=100  
EPOCHS=200  
PATIENCE=100  
SHOW_MISTAKEN_PREDICTIONS=True
```

```
IMG_WIDTH=150  
IMG_HEIGHT=150
```

```
training_datagen = ImageDataGenerator(rescale = 1./255)  
validation_datagen = ImageDataGenerator(rescale = 1./255)
```

  

```
train_generator = training_datagen.flow_from_directory(  
    TRAINING_DIR,  
    target_size=(IMG_WIDTH,IMG_HEIGHT),  
    batch_size=BATCH_SIZE,  
    class_mode='categorical')
```

  

```
validation_generator = validation_datagen.flow_from_directory(  
    VALIDATION_DIR,  
    target_size=(IMG_WIDTH,IMG_HEIGHT),  
    batch_size=BATCH_SIZE,  
    class_mode='categorical',  
    shuffle=False)
```

  

```
number_of_classes=len(list(train_generator.class_indices.keys()))  
model = Sequential([  
    # Note the input shape is the desired size of the image 150x150 with 3 bytes color  
    # This is the first convolution  
    Conv2D(32, (3,3), activation='relu', input_shape=(IMG_WIDTH,IMG_HEIGHT, 3)),  
    MaxPooling2D(2, 2),  
    # The second convolution  
    Conv2D(64, (3,3), activation='relu'),  
    MaxPooling2D(2,2),  
    # The third convolution  
    Conv2D(128, (3,3), activation='relu'),  
    MaxPooling2D(2,2),  
    # The fourth convolution  
    Conv2D(128, (3,3), activation='relu'),  
    MaxPooling2D(2,2),
```

```

# Flatten the results to feed into a DNN
Flatten(),
Dropout(0.5),
# 512 neuron hidden Layer
Dense(512, activation='relu'),
Dense(number_of_classes, activation='softmax')
])

model.compile(loss = 'categorical_crossentropy', optimizer='adam', metrics=[ 'accuracy'])

callbacks = [EarlyStopping(monitor='val_loss', mode='min', patience=PATIENCE),
            ModelCheckpoint(filepath='best_model.h5', monitor='val_loss', mode='min', save_best_only=True, verbose=1)]

history = model.fit_generator(train_generator,
                               epochs=EPOCHS,
                               callbacks=callbacks,
                               validation_data = validation_generator,
                               steps_per_epoch=train_generator.samples // BATCH_SIZE,
                               validation_steps=validation_generator.samples // BATCH_SIZE,
                               verbose = 1)

acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
loss = history.history['loss']
val_loss = history.history['val_loss']

epochs = range(len(acc))

plt.plot(epochs, acc, 'r', label='Training accuracy')
plt.plot(epochs, val_acc, 'b', label='Validation accuracy')
plt.title('Training and validation accuracy')
plt.legend(loc=0)
plt.figure()

plt.plot(epochs, loss, 'r', label='Training Loss')
plt.plot(epochs, val_loss, 'b', label='Validation Loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()

def plot_confusion_matrix(cm,
                         target_names,
                         title='Confusion matrix',
                         cmap=None,
                         normalize=True):
    accuracy = np.trace(cm) / float(np.sum(cm))
    misclass = 1 - accuracy

```

```

if cmap is None:
    # Greys, Purples, Blues, Greens, Oranges, Reds, YlOrBr, YlOrRd, OrRd,
PuRd, RdPu, BuPu, GnBu, PuBu, YlGnBu, PuBuGn, BuGn, YlGn
    cmap = plt.get_cmap('YlGn')

plt.figure(figsize=(8, 6))
plt.imshow(cm, interpolation='nearest', cmap=cmap)
plt.title(title)
plt.colorbar()

if target_names is not None:
    tick_marks = np.arange(len(target_names))
    plt.xticks(tick_marks, target_names, rotation=90)
    plt.yticks(tick_marks, target_names)

if normalize:
    cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]

thresh = cm.max() / 1.5 if normalize else cm.max() / 2
for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
    if normalize:
        plt.text(j, i, "{:0.4f}".format(cm[i, j]),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")
    else:
        plt.text(j, i, "{:,}".format(cm[i, j]),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

plt.tight_layout()
plt.ylabel('True label')
plt.xlabel('Predicted label\naccuracy={:0.4f}; misclass={:0.4f}'.format(accuracy, misclass))
plt.show()

```

```

def results_for(model_file,
                data_generator,
                caption ):
    model = tf.keras.models.load_model(model_file)
    test_loss, test_acc = model.evaluate_generator(data_generator)
    print(caption, ' acc:', test_acc)
    print(caption, ' loss:', test_loss)
    # Confusion matrix
    num_of_samples=data_generator.samples
    batch_size=20
    Y_pred = model.predict_generator(data_generator, num_of_samples // batch_size)
    y_pred = np.argmax(Y_pred, axis=1)
    #print(y_pred)
    #print('Confusion Matrix')
    cm=confusion_matrix(data_generator.classes, y_pred)

```

```

#print(cm)

target_names=data_generator.class_indices.keys()
plot_confusion_matrix(cm,normalize = False,target_names=target_names,title
= "Confusion Matrix")
print('Classification Report')
print('-----')
print(classification_report(data_generator.classes, y_pred, target_names=target_names))

# List the mistaken predictions
if SHOW_MISTAKEN_PREDICTIONS:
    print('\nMistaken predictions')
    print('-----')
    filenames=data_generator.filenames
    errors=np.where(y_pred!=data_generator.classes)[0]
    error_count=len(errors)
    for error in errors:
        predicted=list(data_generator.class_indices.keys())[list(data_generator.class_indices.values()).index(y_pred[error])]
        print("Picture:",filenames[error]," Misprediction ==> ", predicted)

test_datagen = ImageDataGenerator(rescale=1./255)
test_generator = test_datagen.flow_from_directory(TEST_DIR,target_size=(150, 150),shuffle=False,batch_size=500,class_mode='categorical')

results_for('best_model.h5',test_generator,"test")

results_for('best_model.h5',validation_generator,"validation")

```

## Some Mathematical Expressions

The  $i^{th}$  feature map is computed as follows:

$$Y_i^{(l)} = B_i^{(l)} + \sum_{j=1}^{m_1^{(l-1)}} K_{ij}^{(l)} * B_j^{(l-1)}$$

There is a bank of  $m_1$  filters and the output  $Y_i^{(l)}$  of the  $l^{th}$  layer consists of  $m_i^{(l)}$  feature maps of size  $m_2^{(l)} \times m_3^{(l)}$ .

The convolution operation is widely used in digital image processing where the 2D matrix representing the image ( $I$ ) is convolved with the smaller 2D kernel matrix ( $K$ ), then the mathematical formulation with zero padding is given:

$$S_{i,j} = (l * K)_{i,j} = \sum_m \sum_n l_{i,j} \cdot K_{i-m,j-n}$$

The operation of the activation function  $f()$  is as follows:

$$\phi(Y_i^{(l)}) = f\left(B_i^{(l)} + \sum_{j=1}^{m_1^{(l-1)}} K_{ij}^{(l)} * Y_j^{(l-1)}\right)$$

ReLU is the most used activation function for convolution layers. It is mathematically defined as:

$$f(x) = \begin{cases} 0 & \text{if } x < 0 \\ x & \text{if } x \geq 0 \end{cases}$$

Max pooling: Mathematically it has the form:

$$f_{max}(A) = \max_{n \times m}(A_{n \times m})$$