workbook (2)

December 26, 2022

1 Biomedical Image Analysis

[1]:
```
import os
import cv2
import pickle
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from tqdm import tqdm
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import confusion_matrix
from keras.models import Model, load_model
from keras.layers import Dense, Input, Conv2D, MaxPool2D, Flatten
from keras.preprocessing.image import ImageDataGenerator
from sklearn.model_selection import train_test_split
from keras.applications.vgg16 import VGG16
from keras.layers import GlobalAveragePooling2D
from keras.layers import BatchNormalization
from keras.layers import Dropout
from keras.layers import Dense
from keras.optimizers import Adam
from keras.callbacks import ReduceLROnPlateau
from keras.callbacks import ModelCheckpoint
from sklearn.metrics import ConfusionMatrixDisplay
import pandas as pd
```

[2]:
```
def load_normal(norm_path):
    norm_files = np.array(os.listdir(norm_path))
    norm_labels = np.array(['normal']*len(norm_files))

    norm_images = []
    for image in tqdm(norm_files):
        image = cv2.imread(norm_path + image)
        image = cv2.resize(image, dsize=(200,200))
        image = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
        norm_images.append(image)
```

```
    norm_images = np.array(norm_images)
    print(len(norm_images))

    return norm_images, norm_labels
def load_pneumonia(pneu_path):
    pneu_files = np.array(os.listdir(pneu_path))
    pneu_labels = np.array([pneu_file.split('_')[1] for pneu_file in␣
 ↪pneu_files])

    pneu_images = []
    for image in tqdm(pneu_files):
        image = cv2.imread(pneu_path + image)
        image = cv2.resize(image, dsize=(200,200))

        image = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
        pneu_images.append(image)

    pneu_images = np.array(pneu_images)
    X_train = np.append(norm_images, pneu_images, axis=0)
    y_train = np.append(norm_labels, pneu_labels)

    return pneu_images, pneu_labels
```

[3]:
```
norm_images, norm_labels = load_normal('C:/Users/anask/OneDrive/Desktop/
 ↪Diplomski/3.sem/ASUB/chest_xray/chest_xray/train/NORMAL/')
pneu_images, pneu_labels = load_pneumonia('C:/Users/anask/OneDrive/Desktop/
 ↪Diplomski/3.sem/ASUB/chest_xray/chest_xray/train/PNEUMONIA/')
```

```
100%|      | 1341/1341 [00:29<00:00, 46.09it/s]

1341

100%|      | 3875/3875 [00:32<00:00, 120.58it/s]
```

[4]:
```
X_train = np.append(norm_images, pneu_images, axis=0)
y_train = np.append(norm_labels, pneu_labels)
```

[5]:
```
def plot_images(X, y):
    fig, axes = plt.subplots(ncols=7, nrows=2, figsize=(16, 4))

    indices = np.random.choice(len(X), 14)
    counter = 0

    for i in range(2):
        for j in range(7):
            axes[i,j].set_title(y[indices[counter]])
            axes[i,j].imshow(X[indices[counter]], cmap='gray')
            axes[i,j].get_xaxis().set_visible(False)
```

```
            axes[i,j].get_yaxis().set_visible(False)
            counter += 1
    plt.show()
```

[6]:
```
norm_images_test, norm_labels_test = load_normal('C:/Users/anask/OneDrive/
↪Desktop/Diplomski/3.sem/ASUB/chest_xray/chest_xray/test/NORMAL/')
pneu_images_test, pneu_labels_test = load_pneumonia('C:/Users/anask/OneDrive/
↪Desktop/Diplomski/3.sem/ASUB/chest_xray/chest_xray/test/PNEUMONIA/')
```

```
100%|          | 234/234 [00:04<00:00, 56.11it/s]

234

100%|          | 390/390 [00:02<00:00, 131.97it/s]
```

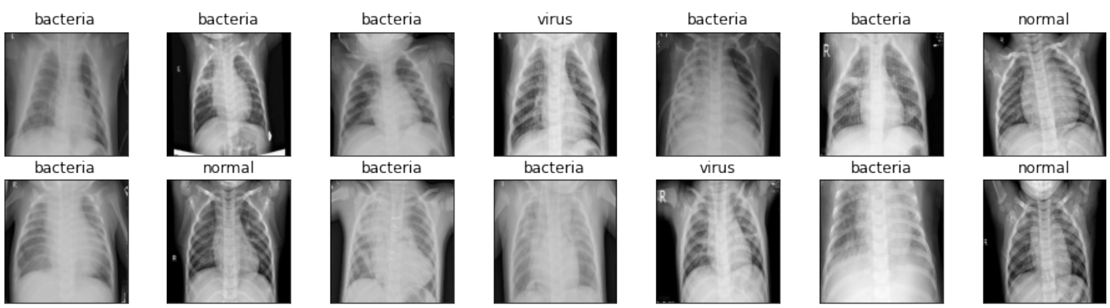
[7]:
```
X_test = np.append(norm_images_test, pneu_images_test, axis=0)
y_test = np.append(norm_labels_test, pneu_labels_test)
```

[128]:
```
with open('pneumonia_data.pickle', 'wb') as f:
    pickle.dump((X_train, X_test, y_train, y_test), f)# Use this to load␣
↪variables
with open('pneumonia_data.pickle', 'rb') as f:
    (X_train, X_test, y_train, y_test) = pickle.load(f)
```

[129]:
```
np.unique(y_train, return_counts=True)
```

[129]:
```
(array(['bacteria', 'normal', 'virus'], dtype='<U8'),
 array([2530, 1341, 1345], dtype=int64))
```

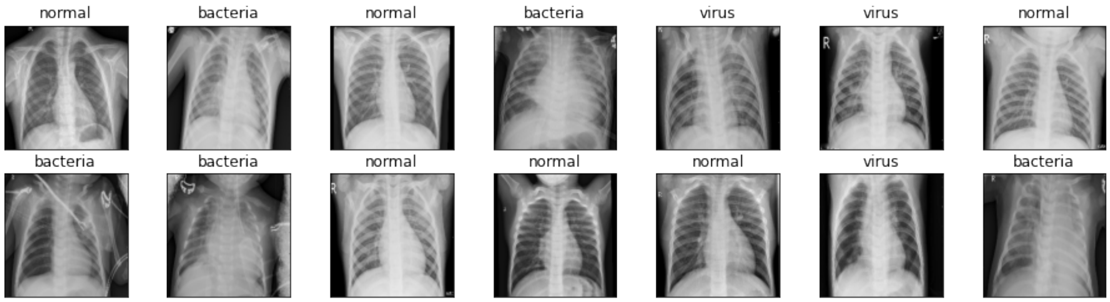
[130]:
```
plot_images(X_train, y_train)
```



[131]:
```
np.unique(y_train, return_counts=True)
```

[131]:
```
(array(['bacteria', 'normal', 'virus'], dtype='<U8'),
 array([2530, 1341, 1345], dtype=int64))
```

[132]:
```
plot_images(X_test, y_test)
```



[133]:
```
y_train = y_train[:, np.newaxis]
y_test = y_test[:, np.newaxis]
```

[133]:
```
array([['normal'],
       ['normal'],
       ['normal'],
       …,
       ['bacteria'],
       ['bacteria'],
       ['bacteria']], dtype='<U8')
```

[135]:
```
one_hot_encoder = OneHotEncoder(sparse=False, handle_unknown = 'error')
```

[136]:
```
y_train_one_hot = one_hot_encoder.fit_transform(y_train)
y_test_one_hot = one_hot_encoder.transform(y_test)
```

[137]:
```
X_train = X_train.reshape(X_train.shape[0], X_train.shape[1], X_train.shape[2], 1)
X_test = X_test.reshape(X_test.shape[0], X_test.shape[1], X_test.shape[2], 1)
```

[138]:
```
datagen = ImageDataGenerator(
        rotation_range = 10,
        zoom_range = 0.1,
        width_shift_range = 0.1,
        height_shift_range = 0.1)
```

[139]:
```
datagen.fit(X_train)
train_gen = datagen.flow(X_train, y_train_one_hot, batch_size=32)
```

[140]:
```
input1 = Input(shape=(X_train.shape[1], X_train.shape[2], 1))

cnn = Conv2D(16, (3, 3), activation='sigmoid', strides=(1, 1),
    padding='same')(input1)
```

```
cnn = Conv2D(32, (3, 3), activation='sigmoid', strides=(1, 1),
    padding='same')(cnn)
cnn = MaxPool2D((2, 2))(cnn)

cnn = Conv2D(16, (2, 2), activation='sigmoid', strides=(1, 1),
    padding='same')(cnn)
cnn = Conv2D(32, (2, 2), activation='sigmoid', strides=(1, 1),
    padding='same')(cnn)
cnn = MaxPool2D((2, 2))(cnn)

cnn = Flatten()(cnn)
cnn = Dense(100, activation='relu')(cnn)
cnn = Dense(50, activation='relu')(cnn)
output1 = Dense(3, activation='softmax')(cnn)

model = Model(inputs=input1, outputs=output1)
```

[141]:
```
model.summary()
```

```
Model: "model_12"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_31 (InputLayer)       [(None, 200, 200, 1)]     0

 conv2d_18 (Conv2D)          (None, 200, 200, 16)      160

 conv2d_19 (Conv2D)          (None, 200, 200, 32)      4640

 max_pooling2d_2 (MaxPooling  (None, 100, 100, 32)     0
 2D)

 conv2d_20 (Conv2D)          (None, 100, 100, 16)      2064

 conv2d_21 (Conv2D)          (None, 100, 100, 32)      2080

 max_pooling2d_3 (MaxPooling  (None, 50, 50, 32)       0
 2D)

 flatten_1 (Flatten)         (None, 80000)             0

 dense_14 (Dense)            (None, 100)               8000100

 dense_15 (Dense)            (None, 50)                5050

 dense_16 (Dense)            (None, 3)                 153
```

```
=================================================================
Total params: 8,014,247
Trainable params: 8,014,247
Non-trainable params: 0
_________________________________________________________________
```

[142]:
```
model.compile(loss='categorical_crossentropy', optimizer='adam',␣
 ↪metrics=['acc'])
```

[143]:
```
history2 = model.fit_generator(train_gen, epochs=30, validation_data=(X_test,␣
 ↪y_test_one_hot))
```

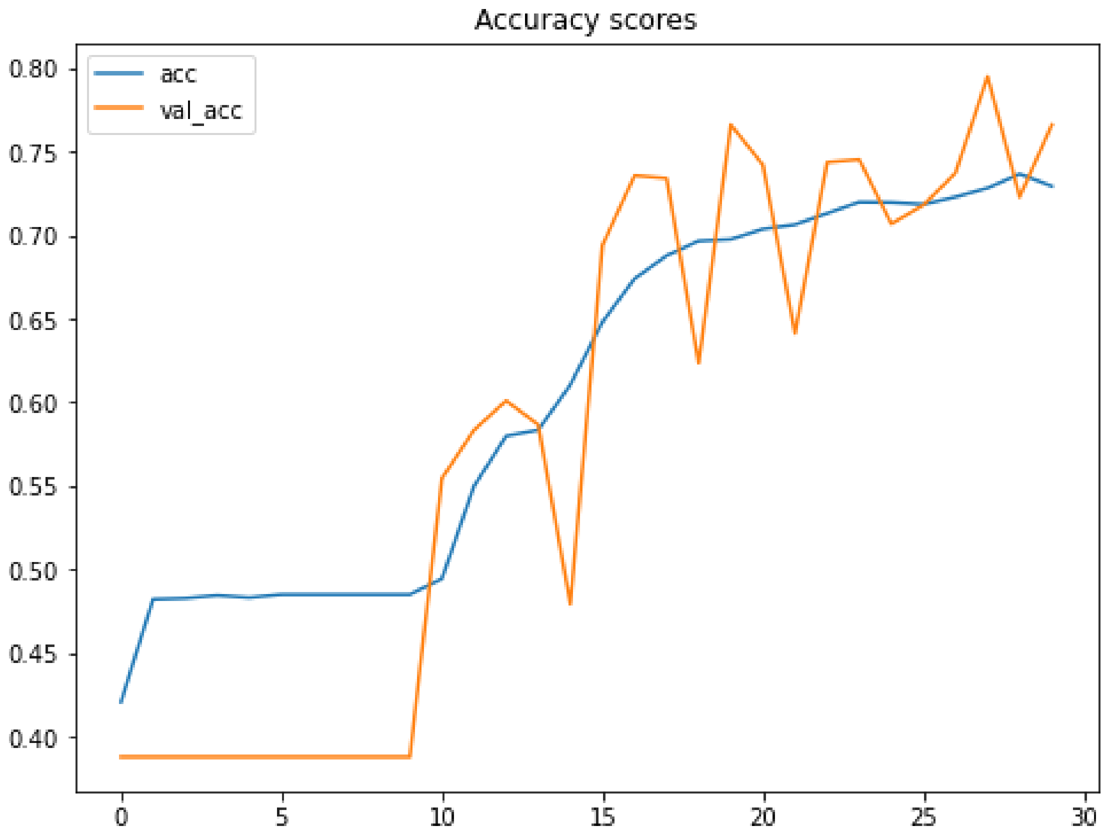
```
Epoch 1/30

C:\Users\anask\AppData\Local\Temp/ipykernel_17632/2115395957.py:1: UserWarning:
`Model.fit_generator` is deprecated and will be removed in a future version.
Please use `Model.fit`, which supports generators.
  history2 = model.fit_generator(train_gen, epochs=30, validation_data=(X_test,
y_test_one_hot))

163/163 [==============================] - 124s 757ms/step - loss: 1.7789 - acc:
0.4206 - val_loss: 1.1401 - val_acc: 0.3878
Epoch 2/30
163/163 [==============================] - 122s 751ms/step - loss: 1.0617 - acc:
0.4822 - val_loss: 1.1351 - val_acc: 0.3878
Epoch 3/30
163/163 [==============================] - 121s 740ms/step - loss: 1.0618 - acc:
0.4827 - val_loss: 1.0873 - val_acc: 0.3878
Epoch 4/30
163/163 [==============================] - 122s 747ms/step - loss: 1.0601 - acc:
0.4845 - val_loss: 1.1182 - val_acc: 0.3878
Epoch 5/30
163/163 [==============================] - 120s 738ms/step - loss: 1.0533 - acc:
0.4831 - val_loss: 1.0932 - val_acc: 0.3878
Epoch 6/30
163/163 [==============================] - 121s 739ms/step - loss: 1.0524 - acc:
0.4850 - val_loss: 1.1081 - val_acc: 0.3878
Epoch 7/30
163/163 [==============================] - 122s 750ms/step - loss: 1.0537 - acc:
0.4850 - val_loss: 1.1283 - val_acc: 0.3878
Epoch 8/30
163/163 [==============================] - 122s 747ms/step - loss: 1.0520 - acc:
0.4850 - val_loss: 1.0967 - val_acc: 0.3878
Epoch 9/30
163/163 [==============================] - 124s 758ms/step - loss: 1.0524 - acc:
0.4850 - val_loss: 1.1112 - val_acc: 0.3878
Epoch 10/30
163/163 [==============================] - 123s 753ms/step - loss: 1.0515 - acc:
0.4850 - val_loss: 1.1007 - val_acc: 0.3878
```

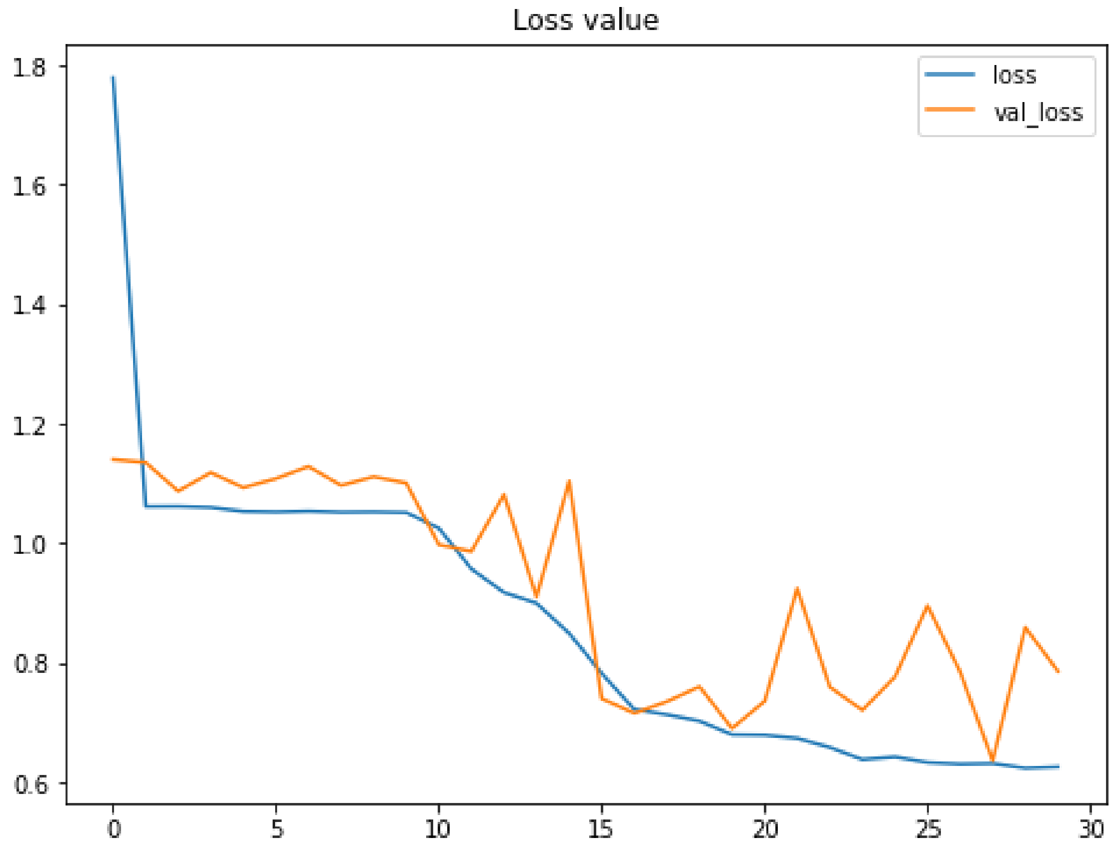
```
Epoch 11/30
163/163 [==============================] - 123s 757ms/step - loss: 1.0251 - acc:
0.4944 - val_loss: 0.9976 - val_acc: 0.5545
Epoch 12/30
163/163 [==============================] - 124s 758ms/step - loss: 0.9572 - acc:
0.5498 - val_loss: 0.9864 - val_acc: 0.5833
Epoch 13/30
163/163 [==============================] - 123s 755ms/step - loss: 0.9175 - acc:
0.5798 - val_loss: 1.0815 - val_acc: 0.6010
Epoch 14/30
163/163 [==============================] - 123s 752ms/step - loss: 0.8997 - acc:
0.5834 - val_loss: 0.9102 - val_acc: 0.5865
Epoch 15/30
163/163 [==============================] - 122s 750ms/step - loss: 0.8493 - acc:
0.6104 - val_loss: 1.1038 - val_acc: 0.4792
Epoch 16/30
163/163 [==============================] - 122s 748ms/step - loss: 0.7823 - acc:
0.6480 - val_loss: 0.7401 - val_acc: 0.6939
Epoch 17/30
163/163 [==============================] - 124s 763ms/step - loss: 0.7219 - acc:
0.6739 - val_loss: 0.7155 - val_acc: 0.7356
Epoch 18/30
163/163 [==============================] - 129s 789ms/step - loss: 0.7132 - acc:
0.6877 - val_loss: 0.7351 - val_acc: 0.7340
Epoch 19/30
163/163 [==============================] - 123s 752ms/step - loss: 0.7024 - acc:
0.6965 - val_loss: 0.7602 - val_acc: 0.6234
Epoch 20/30
163/163 [==============================] - 121s 745ms/step - loss: 0.6798 - acc:
0.6975 - val_loss: 0.6900 - val_acc: 0.7660
Epoch 21/30
163/163 [==============================] - 122s 746ms/step - loss: 0.6792 - acc:
0.7036 - val_loss: 0.7357 - val_acc: 0.7420
Epoch 22/30
163/163 [==============================] - 122s 749ms/step - loss: 0.6737 - acc:
0.7063 - val_loss: 0.9239 - val_acc: 0.6410
Epoch 23/30
163/163 [==============================] - 122s 748ms/step - loss: 0.6585 - acc:
0.7130 - val_loss: 0.7596 - val_acc: 0.7436
Epoch 24/30
163/163 [==============================] - 122s 747ms/step - loss: 0.6383 - acc:
0.7197 - val_loss: 0.7207 - val_acc: 0.7452
Epoch 25/30
163/163 [==============================] - 121s 745ms/step - loss: 0.6427 - acc:
0.7195 - val_loss: 0.7766 - val_acc: 0.7067
Epoch 26/30
163/163 [==============================] - 121s 745ms/step - loss: 0.6333 - acc:
0.7184 - val_loss: 0.8958 - val_acc: 0.7179
```

```
Epoch 27/30
163/163 [==============================] - 122s 750ms/step - loss: 0.6308 - acc:
0.7228 - val_loss: 0.7847 - val_acc: 0.7372
Epoch 28/30
163/163 [==============================] - 122s 745ms/step - loss: 0.6316 - acc:
0.7281 - val_loss: 0.6366 - val_acc: 0.7949
Epoch 29/30
163/163 [==============================] - 121s 744ms/step - loss: 0.6237 - acc:
0.7366 - val_loss: 0.8595 - val_acc: 0.7228
Epoch 30/30
163/163 [==============================] - 121s 744ms/step - loss: 0.6258 - acc:
0.7293 - val_loss: 0.7860 - val_acc: 0.7660
```

[144]:

```
plt.figure(figsize=(8,6))
plt.title('Accuracy scores')
plt.plot(history2.history['acc'])
plt.plot(history2.history['val_acc'])
plt.legend(['acc', 'val_acc'])
plt.show()
plt.figure(figsize=(8,6))
plt.title('Loss value')
plt.plot(history2.history['loss'])
plt.plot(history2.history['val_loss'])
plt.legend(['loss', 'val_loss'])
plt.show()
```


Accuracy scores
acc
val_acc
0.80
0.75
0.70
0.65
0.60
0.55
0.50
0.45
0.40
0
5
10
15
20
25
30



[84]:
```
X_train, X_test, y_train_one_hot, y_test_one_hot = train_test_split(
  X_train, y_train_one_hot, test_size=0.2, random_state = 42)
```

[118]:
```
vgg16 = VGG16(weights='imagenet', include_top=False)
hdf5_save = 'VGG16_Model.hdf5'
annealer = ReduceLROnPlateau(
    monitor='val_accuracy', factor=0.70, patience=5,
    verbose=1, min_lr=1e-4)

checkpoint = ModelCheckpoint(hdf5_save, verbose=1, save_best_only=True)

datagen2 = ImageDataGenerator(rotation_range=360,
                             width_shift_range=0.2,
                             height_shift_range=0.2,
                             zoom_range=0.2,
                             horizontal_flip=True,
                             vertical_flip=True)
datagen2.fit(X_train)
train_gen2 = datagen.flow(X_train, y_train_one_hot, batch_size=32)
```

```python
input = Input(shape=(X_train.shape[1], X_train.shape[2], 1))
x = Conv2D(3, (3, 3), padding='same')(input)

x = vgg16(x)

x = GlobalAveragePooling2D()(x)
x = BatchNormalization()(x)
x = Dropout(0.5)(x)
x = Dense(200, activation='relu')(x)
x = BatchNormalization()(x)
x = Dropout(0.5)(x)

output = Dense(3, activation='softmax', name='root')(x)
model2 = Model(input, output)

optimizer = Adam(lr=0.003, beta_1=0.9, beta_2=0.999,
                     epsilon=0.1, decay=0.0)

model2.compile(loss='categorical_crossentropy',
                  optimizer=optimizer, metrics=['accuracy'])

model2.summary()

history = model2.fit_generator(train_gen2, epochs=30, validation_data=(X_test,
 ↪y_test_one_hot))
```

```
Model: "model_11"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_30 (InputLayer)       [(None, 200, 200, 1)]     0

 conv2d_17 (Conv2D)          (None, 200, 200, 3)       30

 vgg16 (Functional)          (None, None, None, 512)   14714688

 global_average_pooling2d_12  (None, 512)              0
  (GlobalAveragePooling2D)

 batch_normalization_21 (Bat  (None, 512)              2048
 chNormalization)

 dropout_20 (Dropout)        (None, 512)               0

 dense_13 (Dense)            (None, 200)               102600
```

```
 batch_normalization_22 (Bat  (None, 200)              800
 chNormalization)

 dropout_21 (Dropout)        (None, 200)               0

 root (Dense)                (None, 3)                 603

=================================================================
Total params: 14,820,769
Trainable params: 14,819,345
Non-trainable params: 1,424
_________________________________________________________________
Epoch 1/30
```

```
C:\Users\anask\AppData\Local\Temp/ipykernel_17632/3426482288.py:43: UserWarning:
`Model.fit_generator` is deprecated and will be removed in a future version.
Please use `Model.fit`, which supports generators.
  history = model2.fit_generator(train_gen2, epochs=30, validation_data=(X_test,
y_test_one_hot))
```

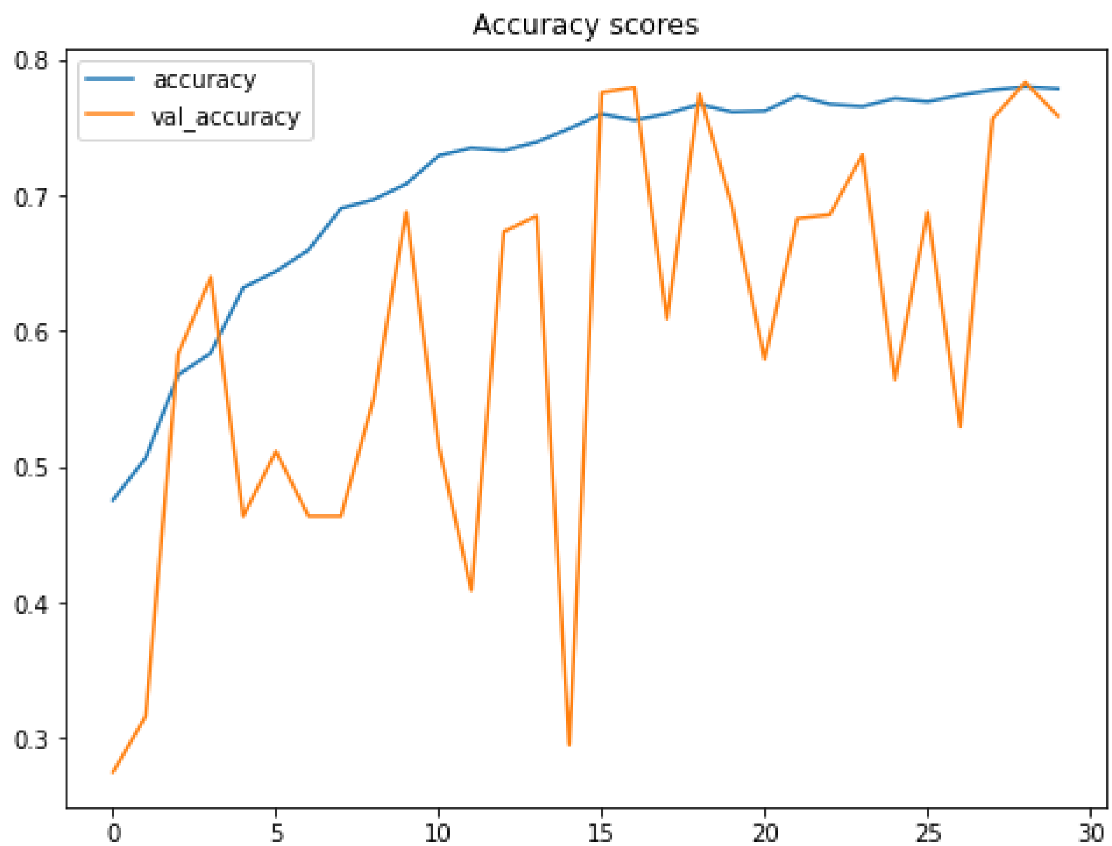
```
131/131 [==============================] - 1419s 11s/step - loss: 1.4240 -
accuracy: 0.4756 - val_loss: 18.0438 - val_accuracy: 0.2749
Epoch 2/30
131/131 [==============================] - 1403s 11s/step - loss: 1.1765 -
accuracy: 0.5065 - val_loss: 6.8709 - val_accuracy: 0.3161
Epoch 3/30
131/131 [==============================] - 1496s 11s/step - loss: 0.9891 -
accuracy: 0.5678 - val_loss: 1.0859 - val_accuracy: 0.5833
Epoch 4/30
131/131 [==============================] - 1416s 11s/step - loss: 0.9183 -
accuracy: 0.5839 - val_loss: 0.8153 - val_accuracy: 0.6398
Epoch 5/30
131/131 [==============================] - 1316s 10s/step - loss: 0.8268 -
accuracy: 0.6321 - val_loss: 2.2517 - val_accuracy: 0.4636
Epoch 6/30
131/131 [==============================] - 1391s 11s/step - loss: 0.7885 -
accuracy: 0.6441 - val_loss: 0.8736 - val_accuracy: 0.5115
Epoch 7/30
131/131 [==============================] - 1427s 11s/step - loss: 0.7516 -
accuracy: 0.6599 - val_loss: 1.9939 - val_accuracy: 0.4636
Epoch 8/30
131/131 [==============================] - 1338s 10s/step - loss: 0.6936 -
accuracy: 0.6906 - val_loss: 1.6949 - val_accuracy: 0.4636
Epoch 9/30
131/131 [==============================] - 1285s 10s/step - loss: 0.6840 -
accuracy: 0.6970 - val_loss: 1.2629 - val_accuracy: 0.5498
Epoch 10/30
131/131 [==============================] - 1288s 10s/step - loss: 0.6635 -
```

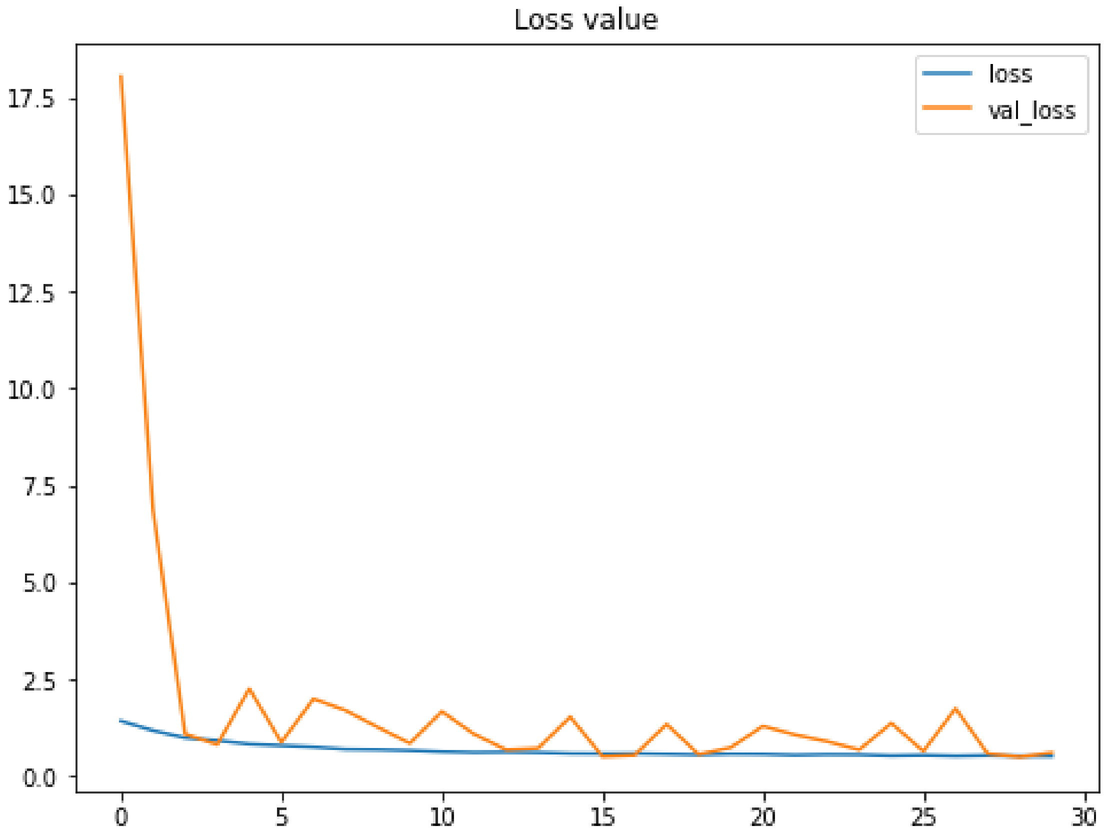
```
accuracy: 0.7085 - val_loss: 0.8478 - val_accuracy: 0.6877
Epoch 11/30
131/131 [==============================] - 1287s 10s/step - loss: 0.6291 -
accuracy: 0.7294 - val_loss: 1.6661 - val_accuracy: 0.5144
Epoch 12/30
131/131 [==============================] - 1277s 10s/step - loss: 0.6100 -
accuracy: 0.7351 - val_loss: 1.0857 - val_accuracy: 0.4090
Epoch 13/30
131/131 [==============================] - 1268s 10s/step - loss: 0.6158 -
accuracy: 0.7332 - val_loss: 0.6816 - val_accuracy: 0.6734
Epoch 14/30
131/131 [==============================] - 1269s 10s/step - loss: 0.6051 -
accuracy: 0.7395 - val_loss: 0.7212 - val_accuracy: 0.6849
Epoch 15/30
131/131 [==============================] - 1266s 10s/step - loss: 0.5831 -
accuracy: 0.7493 - val_loss: 1.5295 - val_accuracy: 0.2950
Epoch 16/30
131/131 [==============================] - 1266s 10s/step - loss: 0.5785 -
accuracy: 0.7601 - val_loss: 0.5082 - val_accuracy: 0.7759
Epoch 17/30
131/131 [==============================] - 1268s 10s/step - loss: 0.5826 -
accuracy: 0.7555 - val_loss: 0.5402 - val_accuracy: 0.7797
Epoch 18/30
131/131 [==============================] - 1269s 10s/step - loss: 0.5691 -
accuracy: 0.7603 - val_loss: 1.3382 - val_accuracy: 0.6092
Epoch 19/30
131/131 [==============================] - 1274s 10s/step - loss: 0.5534 -
accuracy: 0.7673 - val_loss: 0.5601 - val_accuracy: 0.7749
Epoch 20/30
131/131 [==============================] - 1271s 10s/step - loss: 0.5728 -
accuracy: 0.7615 - val_loss: 0.7395 - val_accuracy: 0.6925
Epoch 21/30
131/131 [==============================] - 1261s 10s/step - loss: 0.5671 -
accuracy: 0.7622 - val_loss: 1.2909 - val_accuracy: 0.5795
Epoch 22/30
131/131 [==============================] - 1267s 10s/step - loss: 0.5453 -
accuracy: 0.7735 - val_loss: 1.0680 - val_accuracy: 0.6830
Epoch 23/30
131/131 [==============================] - 1260s 10s/step - loss: 0.5588 -
accuracy: 0.7673 - val_loss: 0.8954 - val_accuracy: 0.6858
Epoch 24/30
131/131 [==============================] - 1262s 10s/step - loss: 0.5543 -
accuracy: 0.7656 - val_loss: 0.6812 - val_accuracy: 0.7299
Epoch 25/30
131/131 [==============================] - 1263s 10s/step - loss: 0.5280 -
accuracy: 0.7716 - val_loss: 1.3649 - val_accuracy: 0.5642
Epoch 26/30
131/131 [==============================] - 1259s 10s/step - loss: 0.5404 -
```

```
accuracy: 0.7692 - val_loss: 0.6417 - val_accuracy: 0.6877
Epoch 27/30
131/131 [==============================] - 1261s 10s/step - loss: 0.5205 -
accuracy: 0.7740 - val_loss: 1.7469 - val_accuracy: 0.5297
Epoch 28/30
131/131 [==============================] - 1261s 10s/step - loss: 0.5345 -
accuracy: 0.7778 - val_loss: 0.5813 - val_accuracy: 0.7567
Epoch 29/30
131/131 [==============================] - 1258s 10s/step - loss: 0.5181 -
accuracy: 0.7802 - val_loss: 0.4950 - val_accuracy: 0.7835
Epoch 30/30
131/131 [==============================] - 1259s 10s/step - loss: 0.5163 -
accuracy: 0.7788 - val_loss: 0.6055 - val_accuracy: 0.7586
```

[120]:

```
plt.figure(figsize=(8,6))
plt.title('Accuracy scores')
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.legend(['accuracy', 'val_accuracy'])
plt.show()
plt.figure(figsize=(8,6))
plt.title('Loss value')
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.legend(['loss', 'val_loss'])
plt.show()
```


Accuracy scores
accuracy
val_accuracy
0.8
0.7
0.6
0.5
0.4
0.3
0
5
10
15
20
25
30


Loss value
loss
val_loss
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
0
5
10
15
20
25
30