workbook (2)

January 9, 2023

1 Biomedical Image Analysis

[4]:
```
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
```

[5]:
```
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
```

[6]:
```
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 [00:28<00:00, 46.69it/s]
```

```
1341
```

```
100%|      | 3875/3875 [00:32<00:00, 119.76it/s]
```

[7]:
```
X_train = np.append(norm_images, pneu_images, axis=0)
y_train = np.append(norm_labels, pneu_labels)
```

[8]:
```
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()
```

[9]:
```
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, 50.39it/s]
```

```
234
```

```
100%|      | 390/390 [00:03<00:00, 109.18it/s]
```

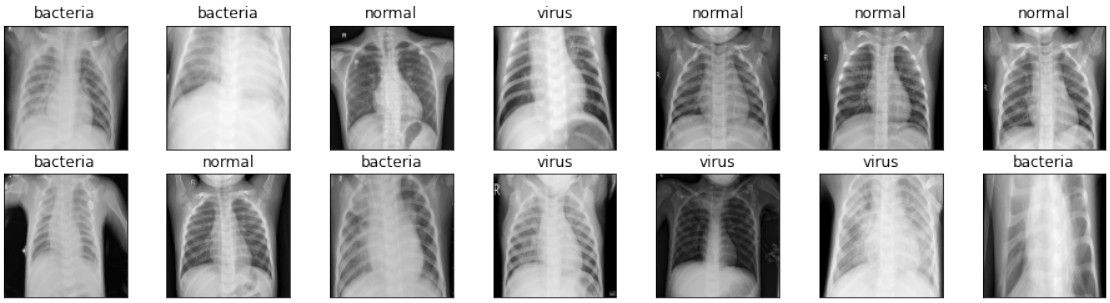
[10]:
```
X_test = np.append(norm_images_test, pneu_images_test, axis=0)
y_test = np.append(norm_labels_test, pneu_labels_test)
```

[11]:
```
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)
```

[12]:
```
np.unique(y_train, return_counts=True)
```

[12]:
```
(array(['bacteria', 'normal', 'virus'], dtype='<U8'),
 array([2530, 1341, 1345], dtype=int64))
```

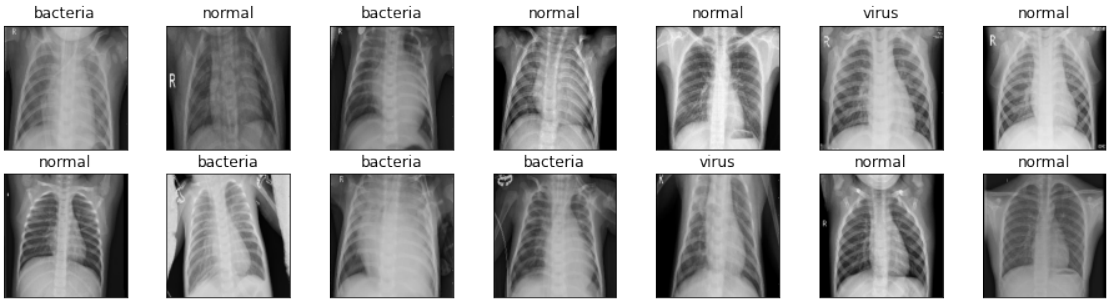
[13]:
```
plot_images(X_train, y_train)
```



[14]:
```
np.unique(y_train, return_counts=True)
```

[14]:
```
(array(['bacteria', 'normal', 'virus'], dtype='<U8'),
 array([2530, 1341, 1345], dtype=int64))
```

[15]:
```
plot_images(X_test, y_test)
```



[16]:
```
y_train = y_train[:, np.newaxis]
y_test = y_test[:, np.newaxis]
```

[17]:
```
one_hot_encoder = OneHotEncoder(sparse=False, handle_unknown = 'error')
```

[18]:
```
y_train_one_hot = one_hot_encoder.fit_transform(y_train)
y_test_one_hot = one_hot_encoder.transform(y_test)
```

[19]:
```
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)
```

[20]:
```
datagen = ImageDataGenerator(
        rotation_range = 10,
        zoom_range = 0.1,
        width_shift_range = 0.1,
        height_shift_range = 0.1)
```

[21]:
```
datagen.fit(X_train)
train_gen = datagen.flow(X_train, y_train_one_hot, batch_size=32)
```

[22]:
```
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)
```

[23]:
```
model.summary()
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 200, 200, 1)]     0

 conv2d (Conv2D)             (None, 200, 200, 16)      160

 conv2d_1 (Conv2D)           (None, 200, 200, 32)      4640

 max_pooling2d (MaxPooling2D  (None, 100, 100, 32)     0
 )

 conv2d_2 (Conv2D)           (None, 100, 100, 16)      2064

 conv2d_3 (Conv2D)           (None, 100, 100, 32)      2080

 max_pooling2d_1 (MaxPooling  (None, 50, 50, 32)       0
 2D)

 flatten (Flatten)           (None, 80000)             0

 dense (Dense)               (None, 100)               8000100

 dense_1 (Dense)             (None, 50)                5050

 dense_2 (Dense)             (None, 3)                 153

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

[24]:
```
model.compile(loss='categorical_crossentropy', optimizer='adam',␣
↪metrics=['acc'])
```

[25]:
```
history2 = model.fit_generator(train_gen, epochs=30, validation_data=(X_test,␣
↪y_test_one_hot))
```

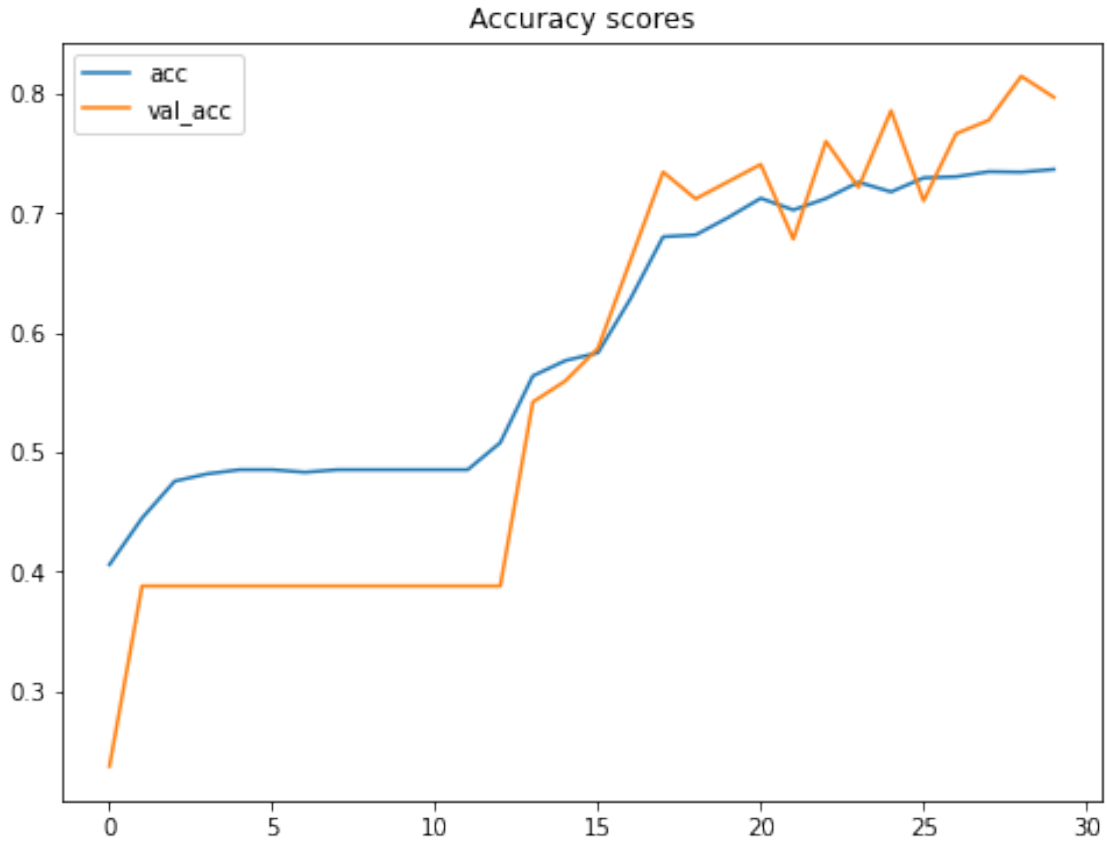
```
C:\Users\anask\AppData\Local\Temp/ipykernel_11724/2115395957.py:1: UserWarning:
`Model.fit_generator` is deprecated and will be removed in a future version.
Please use `Model.fit`, which supports generators.
  history2 = model.fit_generator(train_gen, epochs=30, validation_data=(X_test,
y_test_one_hot))
```

```
Epoch 1/30
163/163 [==============================] - 132s 804ms/step - loss: 1.8028 - acc:
0.4057 - val_loss: 1.1575 - val_acc: 0.2372
Epoch 2/30
163/163 [==============================] - 145s 888ms/step - loss: 1.0995 - acc:
0.4446 - val_loss: 1.1019 - val_acc: 0.3878
Epoch 3/30
163/163 [==============================] - 126s 772ms/step - loss: 1.0729 - acc:
0.4755 - val_loss: 1.1144 - val_acc: 0.3878
Epoch 4/30
163/163 [==============================] - 124s 758ms/step - loss: 1.0598 - acc:
0.4816 - val_loss: 1.1083 - val_acc: 0.3878
Epoch 5/30
163/163 [==============================] - 126s 770ms/step - loss: 1.0560 - acc:
0.4850 - val_loss: 1.0877 - val_acc: 0.3878
Epoch 6/30
163/163 [==============================] - 133s 816ms/step - loss: 1.0559 - acc:
0.4850 - val_loss: 1.1029 - val_acc: 0.3878
Epoch 7/30
163/163 [==============================] - 134s 822ms/step - loss: 1.0557 - acc:
0.4829 - val_loss: 1.1291 - val_acc: 0.3878
Epoch 8/30
163/163 [==============================] - 124s 759ms/step - loss: 1.0542 - acc:
0.4850 - val_loss: 1.1045 - val_acc: 0.3878
Epoch 9/30
163/163 [==============================] - 132s 812ms/step - loss: 1.0525 - acc:
0.4850 - val_loss: 1.0999 - val_acc: 0.3878
Epoch 10/30
163/163 [==============================] - 126s 775ms/step - loss: 1.0519 - acc:
0.4850 - val_loss: 1.1193 - val_acc: 0.3878
Epoch 11/30
163/163 [==============================] - 122s 749ms/step - loss: 1.0533 - acc:
0.4850 - val_loss: 1.1477 - val_acc: 0.3878
Epoch 12/30
163/163 [==============================] - 123s 752ms/step - loss: 1.0503 - acc:
0.4850 - val_loss: 1.1152 - val_acc: 0.3878
Epoch 13/30
163/163 [==============================] - 123s 752ms/step - loss: 1.0031 - acc:
0.5077 - val_loss: 1.0457 - val_acc: 0.3878
```

```
Epoch 14/30
163/163 [==============================] - 123s 751ms/step - loss: 0.9427 - acc:
0.5635 - val_loss: 1.0931 - val_acc: 0.5417
Epoch 15/30
163/163 [==============================] - 135s 827ms/step - loss: 0.9330 - acc:
0.5763 - val_loss: 1.0006 - val_acc: 0.5593
Epoch 16/30
163/163 [==============================] - 133s 818ms/step - loss: 0.9130 - acc:
0.5828 - val_loss: 0.9134 - val_acc: 0.5865
Epoch 17/30
163/163 [==============================] - 128s 785ms/step - loss: 0.8188 - acc:
0.6281 - val_loss: 0.7308 - val_acc: 0.6603
Epoch 18/30
163/163 [==============================] - 132s 811ms/step - loss: 0.7228 - acc:
0.6798 - val_loss: 0.7003 - val_acc: 0.7340
Epoch 19/30
163/163 [==============================] - 123s 757ms/step - loss: 0.7095 - acc:
0.6814 - val_loss: 0.7852 - val_acc: 0.7115
Epoch 20/30
163/163 [==============================] - 123s 752ms/step - loss: 0.6906 - acc:
0.6959 - val_loss: 0.7671 - val_acc: 0.7260
Epoch 21/30
163/163 [==============================] - 122s 746ms/step - loss: 0.6670 - acc:
0.7120 - val_loss: 0.6754 - val_acc: 0.7404
Epoch 22/30
163/163 [==============================] - 121s 743ms/step - loss: 0.6861 - acc:
0.7023 - val_loss: 0.8050 - val_acc: 0.6779
Epoch 23/30
163/163 [==============================] - 124s 760ms/step - loss: 0.6637 - acc:
0.7118 - val_loss: 0.6050 - val_acc: 0.7596
Epoch 24/30
163/163 [==============================] - 121s 743ms/step - loss: 0.6475 - acc:
0.7255 - val_loss: 0.7985 - val_acc: 0.7212
Epoch 25/30
163/163 [==============================] - 121s 743ms/step - loss: 0.6572 - acc:
0.7174 - val_loss: 0.5942 - val_acc: 0.7853
Epoch 26/30
163/163 [==============================] - 121s 739ms/step - loss: 0.6412 - acc:
0.7291 - val_loss: 0.6861 - val_acc: 0.7099
Epoch 27/30
163/163 [==============================] - 121s 742ms/step - loss: 0.6286 - acc:
0.7301 - val_loss: 0.6335 - val_acc: 0.7660
Epoch 28/30
163/163 [==============================] - 121s 743ms/step - loss: 0.6224 - acc:
0.7343 - val_loss: 0.6487 - val_acc: 0.7772
Epoch 29/30
163/163 [==============================] - 121s 743ms/step - loss: 0.6256 - acc:
0.7339 - val_loss: 0.5449 - val_acc: 0.8141
```

```
Epoch 30/30
163/163 [==============================] - 122s 749ms/step - loss: 0.6243 - acc:
0.7362 - val_loss: 0.6014 - val_acc: 0.7965
```

[26]:
```
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()
```



[27]:
```
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)
```

[28]:
```
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)
```

```
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))
```

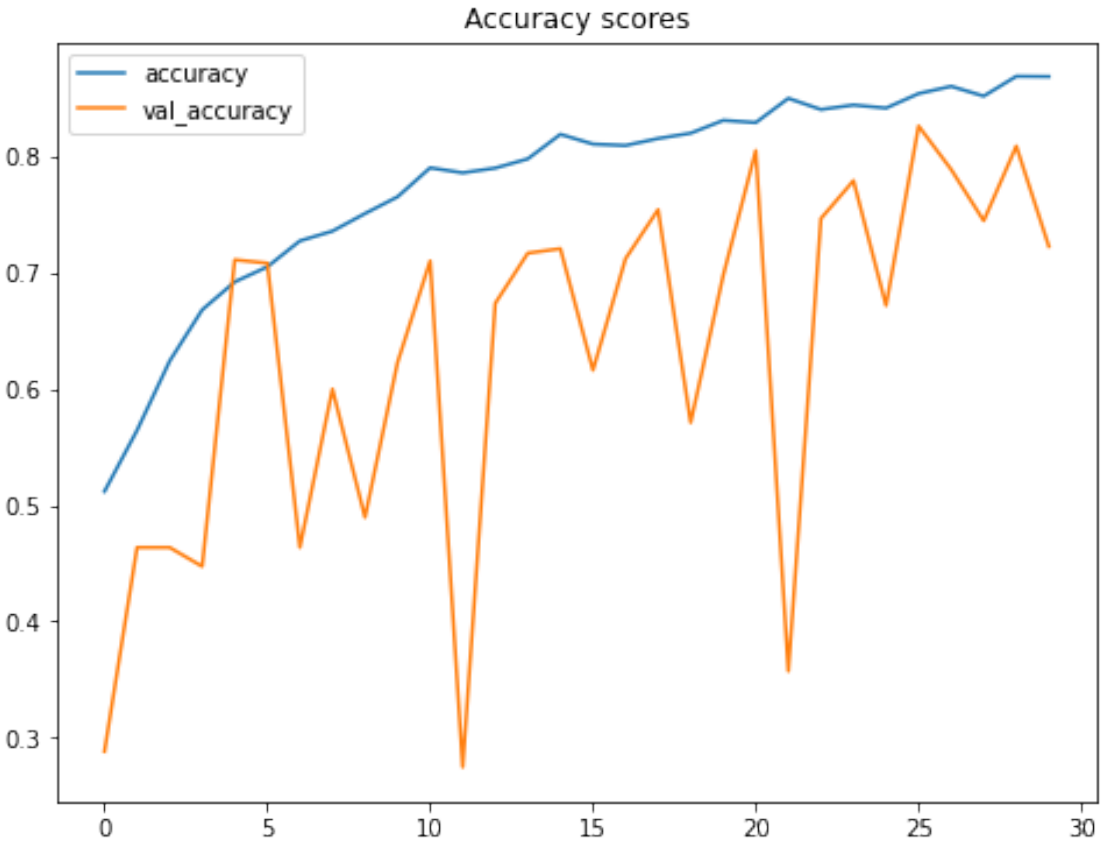
```
Model: "model_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_3 (InputLayer)        [(None, 200, 200, 1)]     0

 conv2d_4 (Conv2D)           (None, 200, 200, 3)       30

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

 global_average_pooling2d (G  (None, 512)              0
 lobalAveragePooling2D)

 batch_normalization (BatchN  (None, 512)              2048
 ormalization)

 dropout (Dropout)           (None, 512)               0

 dense_3 (Dense)             (None, 200)               102600
```

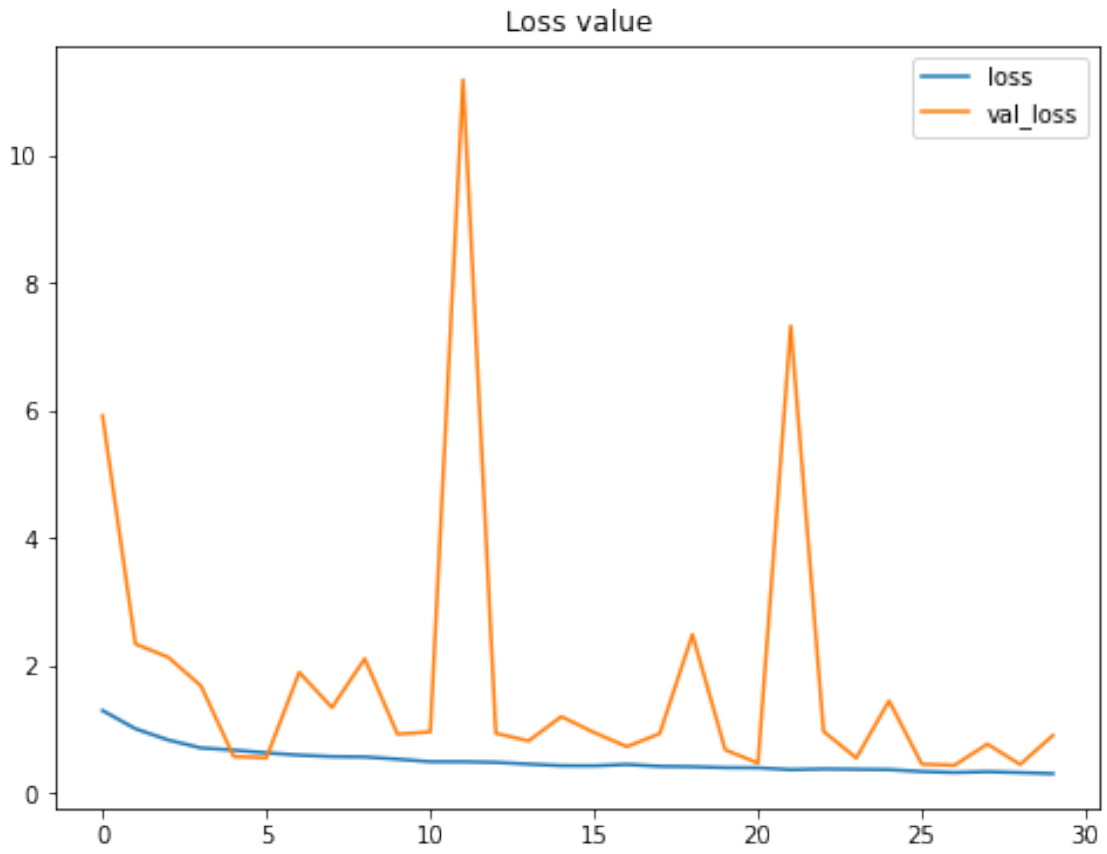
```
 batch_normalization_1 (Batc  (None, 200)              800
 hNormalization)

 dropout_1 (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:\FER\anaconda\lib\site-packages\keras\optimizers\optimizer_v2\adam.py:117:
UserWarning: The `lr` argument is deprecated, use `learning_rate` instead.
  super().__init__(name, **kwargs)
C:\Users\anask\AppData\Local\Temp/ipykernel_11724/3426482288.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 [==============================] - 1334s 10s/step - loss: 1.2980 -
accuracy: 0.5117 - val_loss: 5.9136 - val_accuracy: 0.2883
Epoch 2/30
131/131 [==============================] - 1393s 11s/step - loss: 1.0132 -
accuracy: 0.5642 - val_loss: 2.3422 - val_accuracy: 0.4636
Epoch 3/30
131/131 [==============================] - 1296s 10s/step - loss: 0.8370 -
accuracy: 0.6237 - val_loss: 2.1336 - val_accuracy: 0.4636
Epoch 4/30
131/131 [==============================] - 1326s 10s/step - loss: 0.7122 -
accuracy: 0.6678 - val_loss: 1.6864 - val_accuracy: 0.4473
Epoch 5/30
131/131 [==============================] - 1324s 10s/step - loss: 0.6785 -
accuracy: 0.6918 - val_loss: 0.5777 - val_accuracy: 0.7107
Epoch 6/30
131/131 [==============================] - 1276s 10s/step - loss: 0.6349 -
accuracy: 0.7047 - val_loss: 0.5579 - val_accuracy: 0.7079
Epoch 7/30
131/131 [==============================] - 1381s 11s/step - loss: 0.5992 -
accuracy: 0.7270 - val_loss: 1.8965 - val_accuracy: 0.4636
Epoch 8/30
131/131 [==============================] - 1366s 10s/step - loss: 0.5766 -
accuracy: 0.7354 - val_loss: 1.3455 - val_accuracy: 0.5996
Epoch 9/30
131/131 [==============================] - 1347s 10s/step - loss: 0.5717 -
```

```
accuracy: 0.7505 - val_loss: 2.1108 - val_accuracy: 0.4895
Epoch 10/30
131/131 [==============================] - 1364s 10s/step - loss: 0.5360 -
accuracy: 0.7649 - val_loss: 0.9281 - val_accuracy: 0.6226
Epoch 11/30
131/131 [==============================] - 1390s 11s/step - loss: 0.4965 -
accuracy: 0.7898 - val_loss: 0.9634 - val_accuracy: 0.7098
Epoch 12/30
131/131 [==============================] - 1390s 11s/step - loss: 0.4961 -
accuracy: 0.7855 - val_loss: 11.1811 - val_accuracy: 0.2749
Epoch 13/30
131/131 [==============================] - 1400s 11s/step - loss: 0.4860 -
accuracy: 0.7895 - val_loss: 0.9414 - val_accuracy: 0.6734
Epoch 14/30
131/131 [==============================] - 1372s 11s/step - loss: 0.4592 -
accuracy: 0.7975 - val_loss: 0.8226 - val_accuracy: 0.7165
Epoch 15/30
131/131 [==============================] - 1253s 10s/step - loss: 0.4346 -
accuracy: 0.8186 - val_loss: 1.2035 - val_accuracy: 0.7203
Epoch 16/30
131/131 [==============================] - 1253s 10s/step - loss: 0.4327 -
accuracy: 0.8102 - val_loss: 0.9534 - val_accuracy: 0.6159
Epoch 17/30
131/131 [==============================] - 1249s 10s/step - loss: 0.4533 -
accuracy: 0.8090 - val_loss: 0.7326 - val_accuracy: 0.7117
Epoch 18/30
131/131 [==============================] - 1250s 10s/step - loss: 0.4241 -
accuracy: 0.8150 - val_loss: 0.9361 - val_accuracy: 0.7538
Epoch 19/30
131/131 [==============================] - 1252s 10s/step - loss: 0.4181 -
accuracy: 0.8195 - val_loss: 2.4895 - val_accuracy: 0.5709
Epoch 20/30
131/131 [==============================] - 1245s 10s/step - loss: 0.4036 -
accuracy: 0.8305 - val_loss: 0.6826 - val_accuracy: 0.6973
Epoch 21/30
131/131 [==============================] - 1240s 9s/step - loss: 0.4011 -
accuracy: 0.8286 - val_loss: 0.4755 - val_accuracy: 0.8046
Epoch 22/30
131/131 [==============================] - 1268s 10s/step - loss: 0.3715 -
accuracy: 0.8495 - val_loss: 7.3258 - val_accuracy: 0.3573
Epoch 23/30
131/131 [==============================] - 1238s 9s/step - loss: 0.3832 -
accuracy: 0.8399 - val_loss: 0.9725 - val_accuracy: 0.7462
Epoch 24/30
131/131 [==============================] - 1238s 9s/step - loss: 0.3775 -
accuracy: 0.8437 - val_loss: 0.5535 - val_accuracy: 0.7787
Epoch 25/30
131/131 [==============================] - 1235s 9s/step - loss: 0.3726 -
```

```
accuracy: 0.8411 - val_loss: 1.4503 - val_accuracy: 0.6715
Epoch 26/30
131/131 [==============================] - 1236s 9s/step - loss: 0.3428 -
accuracy: 0.8535 - val_loss: 0.4583 - val_accuracy: 0.8257
Epoch 27/30
131/131 [==============================] - 1235s 9s/step - loss: 0.3276 -
accuracy: 0.8598 - val_loss: 0.4417 - val_accuracy: 0.7883
Epoch 28/30
131/131 [==============================] - 1236s 9s/step - loss: 0.3403 -
accuracy: 0.8514 - val_loss: 0.7734 - val_accuracy: 0.7443
Epoch 29/30
131/131 [==============================] - 1231s 9s/step - loss: 0.3255 -
accuracy: 0.8684 - val_loss: 0.4532 - val_accuracy: 0.8084
Epoch 30/30
131/131 [==============================] - 1232s 9s/step - loss: 0.3094 -
accuracy: 0.8682 - val_loss: 0.9094 - val_accuracy: 0.7222
```

[34]:
```
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



[32]:
```
from sklearn.metrics import confusion_matrix
```

[36]:
```
out = model2.predict(X_test)
```

```
33/33 [==============================] - 77s 2s/step
```

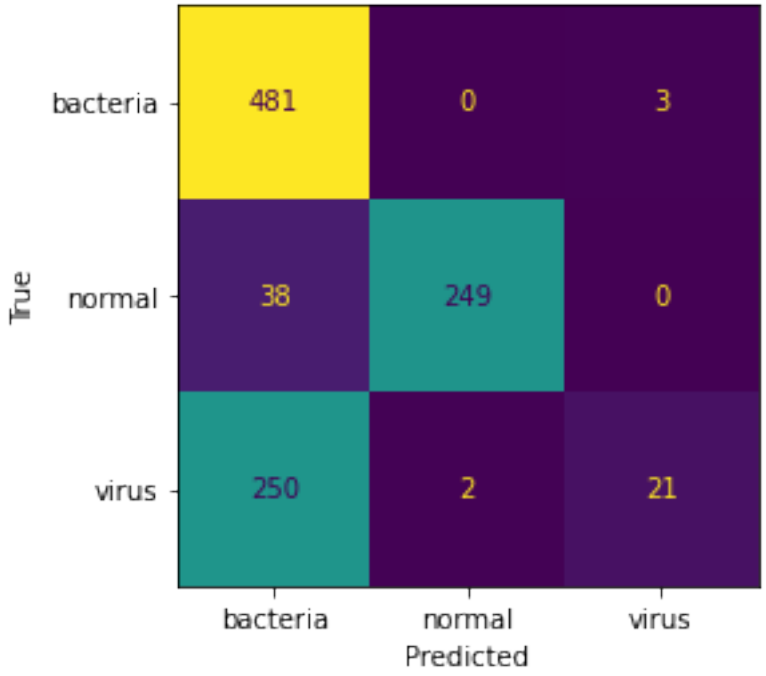
[41]:
```
out
outp = np.where(out > .5, 1, 0)
outp
```

[41]:
```
array([[1, 0, 0],
       [0, 1, 0],
       [1, 0, 0],
       …,
       [1, 0, 0],
       [0, 1, 0],
       [1, 0, 0]])
```

[47]:
```
from sklearn.metrics import ConfusionMatrixDisplay
```

```
cm = ConfusionMatrixDisplay.from_predictions(y_true=y_test_one_hot.
 ↪argmax(axis=1), y_pred=outp.argmax(axis=1), colorbar=False,␣
 ↪display_labels=['bacteria', 'normal', 'virus'])
cm.ax_.set(xlabel='Predicted', ylabel='True')
```

[47]: [Text(0.5, 0, 'Predicted'), Text(0, 0.5, 'True')]



[ ]: