Computer Vision Assignment

Student Name: Stephen pangga

Student Numebr: 629869

Image resizing

In [ ]:
```
from PIL import Image
import os

path = r"C:\Users\Stephen Pangga\Desktop\Computer_vision_v2\All_Test_Tubes/"
new_path = r"C:\Users\Stephen Pangga\Desktop\Computer_vision_v2\Resize"
resize_ratio = 0.5  # where 0.5 is half size

def resize_aspect_fit():
    dirs = os.listdir(path)
    for item in dirs:
        if item == '.jpg':
            continue
        if os.path.isfile(path+item):
            image = Image.open(path+item)
            file_path, extension = os.path.splitext(path+item)

            new_image_height = int(image.size[0] / (1/resize_ratio))
            new_image_length = int(image.size[1] / (1/resize_ratio))

            image = image.resize((new_image_height, new_image_length), Image.ANTIAl
            image.save(file_path + "_small" + extension, 'JPEG', quality=90)

resize_aspect_fit()
```

Data Augmentaion

In [ ]:
```
#%pip install imageio
#%pip install imgaug
#%matplotlib inline
import imageio
import imgaug as ia
import imgaug.augmenters as iaa
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.patches as patches
import matplotlib
import os
import cv2


# C:\Users\Stephen Pangga\Desktop\Computer_vision_v2\Resize tubes Organize Backup
generalpath = "/Users/Stephen Pangga/Desktop/Computer_vision_v2/Resize tubes Organi
inputpath = os.path.join(generalpath)
outputpath = os.path.join(generalpath, 'TT')

imageCountOfLetter = 0

for subdir, dirs, files in os.walk(inputpath):
    for filename in files:
```

```
        if filename.endswith('.jpg'):

            imgpath = os.path.join(subdir, filename)
            filename_stripped = filename.strip('.jpg')
            outputfilepath = os.path.join(subdir, filename_stripped).replace('v1',

            print(imgpath)
            print(filename_stripped)
            print(outputfilepath)


            # 1 Default img
            defaultimg = imageio.imread(imgpath)
            img1 = cv2.resize(defaultimg, (220, 380))
            img = cv2.cvtColor(img1, cv2.COLOR_BGR2RGB)
            cv2.imwrite(outputfilepath + ".jpg", img)

            # 2 Rotate
            rotate=iaa.Affine(rotate=(-30, 30))
            rotated_image=rotate.augment_image(img)
            cv2.imwrite(outputfilepath + "_rotated.jpg", rotated_image)

            # 3 Rotate
            rotate=iaa.Affine(rotate=(30, -30))
            rotated_image=rotate.augment_image(img)
            cv2.imwrite(outputfilepath + "_rotated_2.jpg", rotated_image)

            rotate=iaa.Affine(rotate=(-50, 50))
            rotated_image=rotate.augment_image(img)
            cv2.imwrite(outputfilepath + "_rotated_3.jpg", rotated_image)

            rotate=iaa.Affine(rotate=(50, -50))
            rotated_image=rotate.augment_image(img)
            cv2.imwrite(outputfilepath + "_rotated_4.jpg", rotated_image)

            # 3 Gauss noise
            gaussian_noise=iaa.AdditiveGaussianNoise(10,20)
            noise_image=gaussian_noise.augment_image(img)
            cv2.imwrite(outputfilepath + "_gauss_noise.jpg", noise_image)

            gaussian_noise=iaa.AdditiveGaussianNoise(20,10)
            noise_image=gaussian_noise.augment_image(img)
            cv2.imwrite(outputfilepath + "_gauss_noise_1.jpg", noise_image)

            # 4 Cropping
            crop = iaa.Crop(percent=(0, 0.3)) # crop image
            crop_image = crop.augment_image(img)
            cv2.imwrite(outputfilepath + "_crop.jpg", crop_image)

            # 5 Shearing
            shear = iaa.Affine(shear=(5))
            shear_image = shear.augment_image(img)
            cv2.imwrite(outputfilepath + "_shear.jpg", shear_image)

            # 6 Flipping horizontally
            flip_hr = iaa.Fliplr(p=1.0)
            flip_hr_image = flip_hr.augment_image(img)
            cv2.imwrite(outputfilepath + "_flip_hr.jpg", flip_hr_image)

            # 7 Flip vertically
            flip_vr = iaa.Flipud(p=1.0)
            flip_vr_image= flip_vr.augment_image(img)
            cv2.imwrite(outputfilepath + "_flip_vr.jpg", flip_vr_image)
```

```
            # 8 Change brightness
            contrast = iaa.GammaContrast(gamma=2.0)
            contrast_image = contrast.augment_image(img)
            cv2.imwrite(outputfilepath + "_constrast.jpg", contrast_image)

            # 9 Scaling image
            scale_im = iaa.Affine(scale={"x": (1.5, 1.0), "y": (1.5, 1.0)})
            scale_image = scale_im.augment_image(img)
            cv2.imwrite(outputfilepath + "_scaled.jpg", scale_image)

            # 10 Blur image
            blurred_img = cv2.blur(img, (5, 5))
            cv2.imwrite(outputfilepath + "_blurred.jpg", blurred_img)

            blurred_img = cv2.blur(img, (3, 3))
            cv2.imwrite(outputfilepath + "_blurred3.jpg", blurred_img)
```

Data Division Train - Validation - Test

In [ ]:
```
%pip install split-folders
import os
import splitfolders
input_folder = os.path.dirname("Resize tubes Organize 220x380/")

output = "output_path_no_Plain_220x380v3"

splitfolders.ratio(input_folder, output=output, seed=42, ratio=(.7, .2, .1), group_


# splitfolders.fixed(input_folder, output=output, seed=1337, fixed=(70,10,5), over:
```

Model Training Preparation

In [ ]:
```
# %pip install keras
# %pip install tensorflow
# %pip install image_dataset_loader

import keras
import os
from keras.models import *
from keras.layers import *
from keras.datasets import cifar10
from keras.optimizers import *
from keras.preprocessing.image import ImageDataGenerator
from matplotlib import pyplot as plt
from keras.utils import *
from keras.applications.vgg16 import VGG16
from image_dataset_loader import load


# train_data_dir = os.path.dirname("output_path_no_Plain_220x380v3/train/")
# validation_data_dir = os.path.dirname("output_path_no_Plain_220x380v3/val/")
# test_data_dir = os.path.dirname("output_path_no_Plain_220x380v3/test/")


train_data_dir = os.path.dirname("output_path/train/")
validation_data_dir = os.path.dirname("output_path/val/")
test_data_dir = os.path.dirname("output_path/test/")
```

In [ ]:
```
img_width, img_height = 224, 224
```

```
batch_size = 28

datagenerate_train = ImageDataGenerator(rescale=1.0/255, samplewise_center=True)

train_generator = datagenerate_train.flow_from_directory(train_data_dir,
                                                         target_size=(img_width,img_height)
                                                          batch_size=batch_size,
                                                          #subset="training",
                                                          class_mode='categorical')

datagenerate_validation = ImageDataGenerator(rescale=1.0/255, samplewise_center=Tru

validation_generator = datagenerate_validation.flow_from_directory(validation_data_
                                                                   target_size=(img_width,img_
                                                                   batch_size=batch_size,
                                                                   #subset="validation",
                                                                   class_mode='categorical')



print(train_generator)
print(validation_generator)
# print(test_generator)
```

```
Found 816 images belonging to 7 classes.
Found 101 images belonging to 7 classes.
<keras.preprocessing.image.DirectoryIterator object at 0x000001650A0A5850>
<keras.preprocessing.image.DirectoryIterator object at 0x0000016504588D90>
```

The Model

In [ ]:

```
def define_VGGmodel():

    model = VGG16(include_top=False, input_shape=(img_width, img_height, 3))

    for layer in model.layers:
        layer.trainable = False

    flat1 = Flatten()(model.layers[-1].output)

    class1 = Dense(128, activation='relu', kernel_initializer='he_uniform')(flat1)

    output = Dense(7, activation='softmax')(class1)

    model = Model(inputs=model.inputs, outputs=output)

    #opt = SGD(lr=0.001, momentum=0.9)

    model.compile(optimizer='Adam', loss='categorical_crossentropy', metrics=['cate

    return model

model = define_VGGmodel()
model.summary()
```

```
Model: "model_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_2 (InputLayer)        [(None, 224, 224, 3)]     0

 block1_conv1 (Conv2D)       (None, 224, 224, 64)      1792

 block1_conv2 (Conv2D)       (None, 224, 224, 64)      36928

 block1_pool (MaxPooling2D)  (None, 112, 112, 64)      0

 block2_conv1 (Conv2D)       (None, 112, 112, 128)     73856

 block2_conv2 (Conv2D)       (None, 112, 112, 128)     147584

 block2_pool (MaxPooling2D)  (None, 56, 56, 128)       0

 block3_conv1 (Conv2D)       (None, 56, 56, 256)       295168

 block3_conv2 (Conv2D)       (None, 56, 56, 256)       590080

 block3_conv3 (Conv2D)       (None, 56, 56, 256)       590080

 block3_pool (MaxPooling2D)  (None, 28, 28, 256)       0

 block4_conv1 (Conv2D)       (None, 28, 28, 512)       1180160

 block4_conv2 (Conv2D)       (None, 28, 28, 512)       2359808

 block4_conv3 (Conv2D)       (None, 28, 28, 512)       2359808

 block4_pool (MaxPooling2D)  (None, 14, 14, 512)       0

 block5_conv1 (Conv2D)       (None, 14, 14, 512)       2359808

 block5_conv2 (Conv2D)       (None, 14, 14, 512)       2359808

 block5_conv3 (Conv2D)       (None, 14, 14, 512)       2359808

 block5_pool (MaxPooling2D)  (None, 7, 7, 512)         0

 flatten_1 (Flatten)         (None, 25088)             0

 dense_2 (Dense)             (None, 128)               3211392

 dense_3 (Dense)             (None, 7)                 903

=================================================================
Total params: 17,926,983
Trainable params: 3,212,295
Non-trainable params: 14,714,688
_________________________________________________________________
```

In [ ]:
```python
from keras import callbacks
earlystopping = callbacks.EarlyStopping(monitor ="val_loss",
                                        mode ="min", patience = 5,
                                        restore_best_weights = True)
```

In [ ]:
```python
history = model.fit(train_generator, steps_per_epoch=len(train_generator), validat
 validation_steps=len(validation_generator), epochs=20, verbose=1, shuffle=False, 
```

```
Epoch 1/20
30/30 [==============================] - 87s 3s/step - loss: 2.8826 - categorical_
accuracy: 0.2132 - val_loss: 1.7610 - val_categorical_accuracy: 0.2772
Epoch 2/20
30/30 [==============================] - 85s 3s/step - loss: 1.5195 - categorical_
accuracy: 0.4118 - val_loss: 1.4664 - val_categorical_accuracy: 0.3762
Epoch 3/20
30/30 [==============================] - 82s 3s/step - loss: 1.1327 - categorical_
accuracy: 0.6998 - val_loss: 1.1365 - val_categorical_accuracy: 0.6634
Epoch 4/20
30/30 [==============================] - 80s 3s/step - loss: 0.8550 - categorical_
accuracy: 0.8297 - val_loss: 0.9714 - val_categorical_accuracy: 0.7426
Epoch 5/20
30/30 [==============================] - 82s 3s/step - loss: 0.6739 - categorical_
accuracy: 0.8725 - val_loss: 0.8603 - val_categorical_accuracy: 0.7327
Epoch 6/20
30/30 [==============================] - 80s 3s/step - loss: 0.5375 - categorical_
accuracy: 0.8909 - val_loss: 0.7018 - val_categorical_accuracy: 0.8713
Epoch 7/20
30/30 [==============================] - 79s 3s/step - loss: 0.4243 - categorical_
accuracy: 0.9277 - val_loss: 0.6256 - val_categorical_accuracy: 0.8416
Epoch 8/20
30/30 [==============================] - 80s 3s/step - loss: 0.3339 - categorical_
accuracy: 0.9522 - val_loss: 0.5824 - val_categorical_accuracy: 0.8416
Epoch 9/20
30/30 [==============================] - 80s 3s/step - loss: 0.2777 - categorical_
accuracy: 0.9669 - val_loss: 0.4947 - val_categorical_accuracy: 0.8713
Epoch 10/20
30/30 [==============================] - 81s 3s/step - loss: 0.2219 - categorical_
accuracy: 0.9816 - val_loss: 0.4690 - val_categorical_accuracy: 0.9109
Epoch 11/20
30/30 [==============================] - 80s 3s/step - loss: 0.1745 - categorical_
accuracy: 0.9890 - val_loss: 0.4478 - val_categorical_accuracy: 0.8515
Epoch 12/20
30/30 [==============================] - 80s 3s/step - loss: 0.1473 - categorical_
accuracy: 0.9975 - val_loss: 0.3961 - val_categorical_accuracy: 0.8911
Epoch 13/20
30/30 [==============================] - 81s 3s/step - loss: 0.1226 - categorical_
accuracy: 0.9951 - val_loss: 0.3898 - val_categorical_accuracy: 0.9109
Epoch 14/20
30/30 [==============================] - 80s 3s/step - loss: 0.1050 - categorical_
accuracy: 0.9975 - val_loss: 0.3543 - val_categorical_accuracy: 0.9109
Epoch 15/20
30/30 [==============================] - 81s 3s/step - loss: 0.0876 - categorical_
accuracy: 0.9988 - val_loss: 0.3392 - val_categorical_accuracy: 0.8911
Epoch 16/20
30/30 [==============================] - 81s 3s/step - loss: 0.0740 - categorical_
accuracy: 0.9988 - val_loss: 0.3395 - val_categorical_accuracy: 0.8812
Epoch 17/20
30/30 [==============================] - 87s 3s/step - loss: 0.0651 - categorical_
accuracy: 1.0000 - val_loss: 0.3187 - val_categorical_accuracy: 0.9208
Epoch 18/20
30/30 [==============================] - 81s 3s/step - loss: 0.0617 - categorical_
accuracy: 1.0000 - val_loss: 0.3216 - val_categorical_accuracy: 0.8812
Epoch 19/20
30/30 [==============================] - 80s 3s/step - loss: 0.0498 - categorical_
accuracy: 1.0000 - val_loss: 0.3154 - val_categorical_accuracy: 0.8812
Epoch 20/20
30/30 [==============================] - 81s 3s/step - loss: 0.0437 - categorical_
accuracy: 1.0000 - val_loss: 0.3250 - val_categorical_accuracy: 0.9010
```

In [ ]:

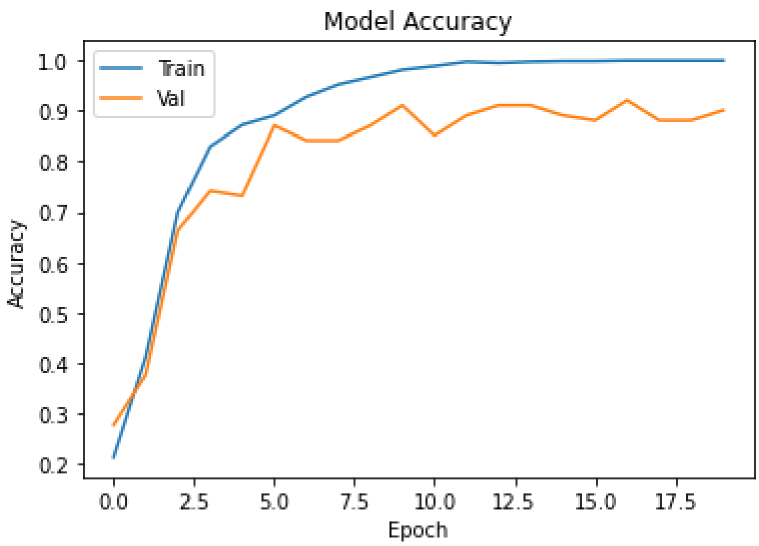
```
print(history.history)
```

{'loss': [2.882565975189209, 1.5194791555404663, 1.1327366828918457, 0.8550347685813904, 0.6738737225532532, 0.5374535322189331, 0.42425525188446045, 0.3338940143585205, 0.27769342064857483, 0.22190436720848083, 0.17446686327457428, 0.14725792407989502, 0.1226036474108696, 0.1049560010433197, 0.087623231112957, 0.07395507395267487, 0.06513470411300659, 0.0616726316511631, 0.0498480498790741, 0.043675608932971954], 'categorical_accuracy': [0.2132352888584137, 0.4117647111415863, 0.6997548937797546, 0.8296568393707275, 0.8725489974021912, 0.8909313678741455, 0.9276960492134094, 0.9522058963775635, 0.966911792755127, 0.9816176295280457, 0.9889705777168274, 0.9975489974021912, 0.9950980544090271, 0.9975489974021912, 0.998774528503418, 0.998774528503418, 1.0, 1.0, 1.0, 1.0], 'val_loss': [1.7610087394714355, 1.4664227962493896, 1.136460542678833, 0.9714139699935913, 0.8603437542915344, 0.7017602324485779, 0.6255902647972107, 0.5824043154716492, 0.49471667408943176, 0.46903523802757263, 0.44778385758399963, 0.3960905969142914, 0.3898434638977051, 0.3543257713317871, 0.33916419744491577, 0.3394950330257416, 0.31873181462287903, 0.32155048847198486, 0.31542450189590454, 0.3250230550765991], 'val_categorical_accuracy': [0.2772277295589447, 0.3762376308441162, 0.6633663177490234, 0.7425742745399475, 0.7326732873916626, 0.8712871074676514, 0.8415841460227966, 0.8415841460227966, 0.8712871074676514, 0.9108911156654358, 0.8514851331710815, 0.8910890817642212, 0.9108911156654358, 0.9108911156654358, 0.8910890817642212, 0.8811880946159363, 0.9207921028137207, 0.8811880946159363, 0.8811880946159363, 0.9009901285171509]}

Diagnostic plot

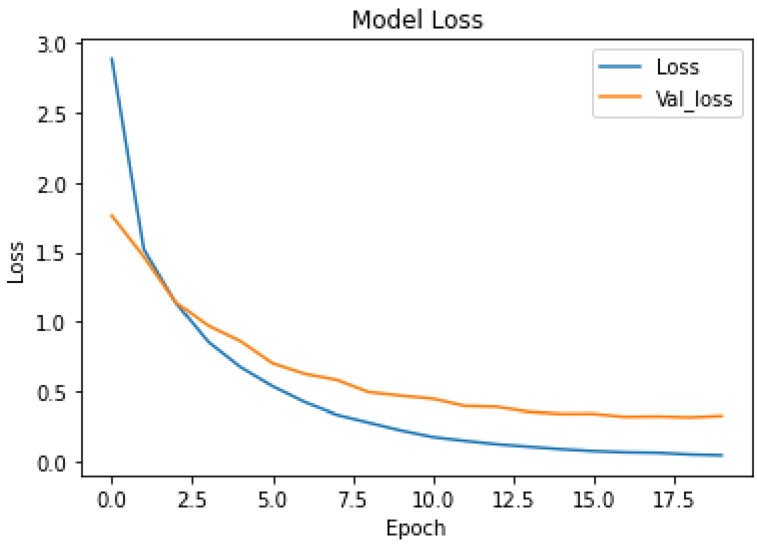
In [ ]:

```
plt.plot(history.history['categorical_accuracy'])
plt.plot(history.history['val_categorical_accuracy'])
plt.title('Model Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val_loss'], loc='upper left')
plt.show()
```



In [ ]:

```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Loss', 'Val_loss'], loc='upper right')
plt.show()
```



In [ ]:
```
print('Validation image - evaluation')
_, acc = model.evaluate(validation_generator, steps=len(validation_generator), verl
print('accuracy score: ', acc*100 )
```

```
Validation image - evaluation
4/4 [==============================] - 10s 2s/step - loss: 0.3250 - categorical_ac
curacy: 0.9010
accuracy score:  90.09901285171509
```

In [ ]:
```
# print('Test image - evaluation')
# _, acc = model.evaluate(test_generator, steps=len(test_generator), verbose=1)
# print('accuracy score: ', acc*100 )
```

Testing

In [ ]:
```
import numpy as np
from sklearn.metrics import confusion_matrix
from sklearn import metrics
# test_data_dir = os.path.dirname("output_path_no_Plain_220x380v1/train-test/")

datagenerate_test = ImageDataGenerator(rescale=1.0/255, samplewise_center=True)

test_generator = datagenerate_test.flow_from_directory(test_data_dir,
                                                target_size=(img_width,img_height)
                                                batch_size=batch_size,
                                                #subset="validation",
                                                class_mode='categorical')
```

```
Found 103 images belonging to 7 classes.
```

In [ ]:
```
print('Test image - evaluation')
_, acc = model.evaluate(test_generator, steps=len(test_generator), verbose=1)
print('accuracy score: ', acc*100 )
```

```
Test image - evaluation
4/4 [==============================] - 9s 2s/step - loss: 0.2666 - categorical_acc
uracy: 0.9320
accuracy score:  93.20388436317444
```

In [ ]:
```
Y_pred = model.predict(test_generator)
y_pred = np.argmax(Y_pred, axis=1)
print('accuracy: ', metrics.accuracy_score(y_pred,test_generator.classes))
```

```
4/4 [==============================] - 9s 2s/step
accuracy:  0.1553398058252427
```

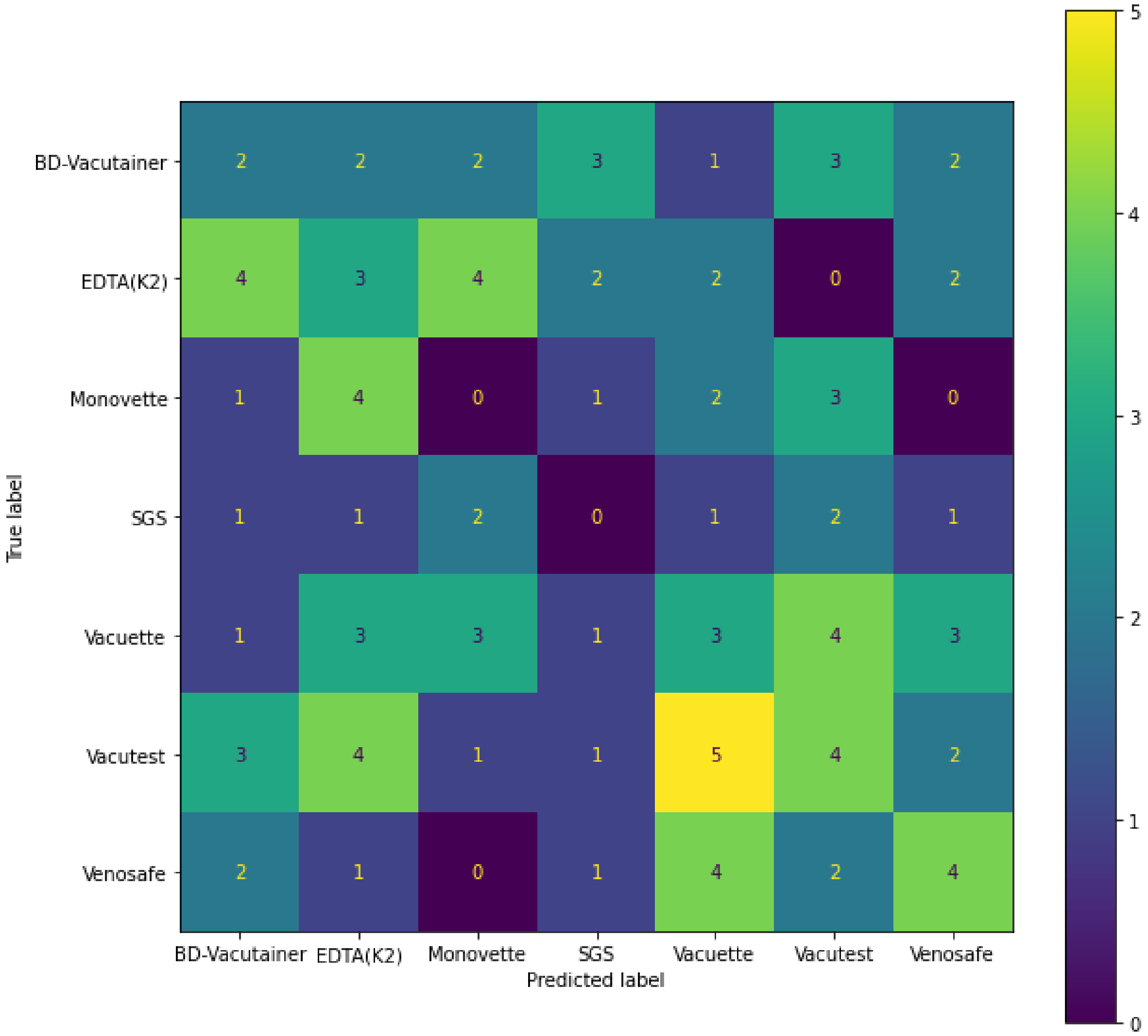
In [ ]:
```
print('Confusion Matrix')
print(confusion_matrix(y_pred, test_generator.classes))
```

```
Confusion Matrix
[[2 2 2 3 1 3 2]
 [4 3 4 2 2 0 2]
 [1 4 0 1 2 3 0]
 [1 1 2 0 1 2 1]
 [1 3 3 1 3 4 3]
 [3 4 1 1 5 4 2]
 [2 1 0 1 4 2 4]]
```

In [ ]:
```
import seaborn as sns
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

cm = confusion_matrix(y_pred, test_generator.classes)
cmd = ConfusionMatrixDisplay(cm, display_labels=[ 'BD-Vacutainer', 'EDTA(K2)', 'Mo
fig, ax = plt.subplots(figsize=(10,10))
plt.grid(False)
cmd.plot(ax=ax)
```

Out[ ]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1651675dd60>



In [ ]:
```
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report

print('Accuracy Score :', accuracy_score(y_pred, test_generator.classes))
print ('Report : ')
target_names = ['BD-Vacutainer', 'EDTA(K2)', 'Monovette', 'SGS', 'Vacuette' , 'Vac
print (classification_report(y_pred, test_generator.classes, target_names=target_n
```

```
Accuracy Score : 0.1553398058252427
Report :
              precision    recall  f1-score   support

BD-Vacutainer       0.14      0.13      0.14        15
     EDTA(K2)       0.17      0.18      0.17        17
    Monovette       0.00      0.00      0.00        11
          SGS       0.00      0.00      0.00         8
     Vacuette       0.17      0.17      0.17        18
     Vacutest       0.22      0.20      0.21        20
     Venosafe       0.29      0.29      0.29        14

     accuracy                           0.16       103
    macro avg       0.14      0.14      0.14       103
 weighted avg       0.16      0.16      0.16       103
```

The Accuracy score is 15.53%, this could be due to the image. One of the plausible issues i can think of that cause such a low accuracy is the fact that maybe the augmented image type has not been since by the model.