```
#%cd
#shutil.rmtree('/content/hands_dataset', ignore_errors=True) #non usarloo
```

```
%cd
%cd ../content
!pwd
```

```
/root
/content
/content
```

```
import numpy as np
import math
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Activation, Dense, Flatten, BatchNormalization, Conv2D, M
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.metrics import categorical_crossentropy
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications import VGG16
from tensorflow.keras.applications.vgg16 import preprocess_input, decode_predictions
from sklearn.metrics import confusion_matrix
from tensorflow.keras.models import Model
from sklearn.metrics import confusion_matrix
import itertools
import itertools
import os
import shutil
import random
import glob
import matplotlib.pyplot as plt
import warnings
```

```
def path_join(dirname, filenames):
    return [os.path.join(dirname, filename) for filename in filenames]
```

```
!pwd

!git clone https://github.com/tesiiscomingson/hands_dataset.git
```

```
/content
Cloning into 'hands_dataset'...
remote: Enumerating objects: 2696, done.
remote: Total 2696 (delta 0), reused 0 (delta 0), pack-reused 2696
Receiving objects: 100% (2696/2696), 22.06 MiB | 32.09 MiB/s, done.
Resolving deltas: 100% (863/863), done.
```

```
%cd hands_dataset
!ls
```

```
/content/hands_dataset
Dataset  Examples  LICENSE  README.md
```

```
!rm -rf Examples  LICENSE  README.md
!ls
```

```
Dataset
```

```
dir_path = os.path.dirname(os.path.realpath('FT_mobilenet.ipynb'))
print(dir_path)
```

```
/content/hands_dataset
```

```
!pwd
```

```
/content/hands_dataset
```

```
%cd /content/hands_dataset/Dataset/
%mkdir train
%mkdir test
%mkdir valid
%mv 0/ 1/ 2 / 3/ 4/ 5/ 6/ 7/ 8/ 9/ train/
```

```
/content/hands_dataset/Dataset
mv: cannot move '/' to 'train': Device or resource busy
```

```
#%cd -
!pwd
%cd valid
%mkdir 0/ 1/ 2 / 3/ 4/ 5/ 6/ 7/ 8/ 9/
%cd ../test
%mkdir 0/ 1/ 2 / 3/ 4/ 5/ 6/ 7/ 8/ 9/
```

```
/content/hands_dataset/Dataset
/content/hands_dataset/Dataset/valid
mkdir: cannot create directory ‘/’: File exists
/content/hands_dataset/Dataset/test
mkdir: cannot create directory ‘/’: File exists
```

```
!pwd
```

```
/content/hands_dataset/Dataset/test
```

```
%%bash
cd ../train
for ((i=0; i<=9; i++)); do
  a=$(find $i/ -type f | shuf -n 30)
  mv $a ../valid/$i/
  b=$(find $i/ -type f | shuf -n 5)
  mv $b ../test/$i/
done
```

```
%cd ../..
!pwd
```

```
/content/hands_dataset
/content/hands_dataset
```

```
train_path = 'Dataset/train'
valid_path = 'Dataset/valid'
test_path = 'Dataset/test'
```

```
train_batches = ImageDataGenerator(preprocessing_function=keras.applications.mobilenet.prepro
    train_path, target_size=(224, 224), batch_size=10)
valid_batches = ImageDataGenerator(preprocessing_function=keras.applications.mobilenet.prepro
    valid_path, target_size=(224, 224), batch_size=10)
test_batches = ImageDataGenerator(preprocessing_function=keras.applications.mobilenet.preproc
    test_path, target_size=(224, 224), batch_size=10, shuffle=False)
```

```
Found 2172 images belonging to 10 classes.
Found 300 images belonging to 10 classes.
Found 50 images belonging to 10 classes.
```

```
model = VGG16(include_top=True, weights='imagenet')
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16
553467904/553467096 [==============================] - 3s 0us/step
```

```
input_shape = model.layers[0].output_shape[0][1:3]
```

```
datagen_train = ImageDataGenerator(
      rescale=1./255,
      brightness_range=[0.7,1.1],
      rotation_range=20,
      width_shift_range=0.1,
      height_shift_range=0.1,
      shear_range=0.1,
      zoom_range=[0.9, 1.2],
      horizontal_flip=False
```

```
      horizontal_flip=False,
      vertical_flip=False,
      fill_mode='nearest')
```

```
datagen_test = ImageDataGenerator(rescale=1./255)
```

```
batch_size = 20
```

We can save the randomly transformed images during training, so as to inspect whether they have been overly distorted, so we have to adjust the parameters for the data-generator above.

```
if True:
    save_to_dir = None
else:
    save_to_dir='augmented_images/'
```

```
generator_train = datagen_train.flow_from_directory(directory=train_path,
                                                    target_size=input_shape,
                                                    batch_size=batch_size,
                                                    shuffle=True,
                                                    save_to_dir=save_to_dir)
```

```
Found 2172 images belonging to 10 classes.
```

```
generator_test = datagen_test.flow_from_directory(directory=valid_path,
                                                  target_size=input_shape,
                                                  batch_size=batch_size,
                                                  shuffle=False)
```

```
Found 300 images belonging to 10 classes.
```

```
steps_test = generator_test.n / batch_size
steps_test
```

```
15.0
```

```
image_paths_train = path_join(train_path, generator_train.filenames)
image_paths_test = path_join(valid_path, generator_test.filenames)
```

```
cls_train = generator_train.classes
cls_test = generator_test.classes
```

```
class_names = list(generator_train.class_indices.keys())
```

```
class_names
```

```
['0', '1', '2', '3', '4', '5', '6', '7', '8', '9']
```

```
num_classes = generator_train.num_classes
num_classes
```

```
10
```

```
model.summary()
```

```
Model: "vgg16"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (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 (Flatten)            (None, 25088)             0
```

```
_________________________________________________________________
fc1 (Dense)                  (None, 4096)              102764544
_________________________________________________________________
fc2 (Dense)                  (None, 4096)              16781312
_________________________________________________________________
predictions (Dense)          (None, 1000)              4097000
=================================================================
Total params: 138,357,544
Trainable params: 138,357,544
Non-trainable params: 0
_________________________________________________________________
```

```
transfer_layer = model.get_layer('block5_pool')
```

```
transfer_layer.output
```

```
<KerasTensor: shape=(None, 7, 7, 512) dtype=float32 (created by layer 'block5_pool')>
```

```
conv_model = Model(inputs=model.input,
                   outputs=transfer_layer.output)
```

```
# Start a new Keras Sequential model.
new_model = Sequential()

# Add the convolutional part of the VGG16 model from above.
new_model.add(conv_model)

# Flatten the output of the VGG16 model because it is from a
# convolutional layer.
new_model.add(Flatten())

# Add a dense layer.
# This is for combining features that the VGG16 model has
# recognized in the image.
new_model.add(Dense(1024, activation='relu'))

# Add a dropout-layer which may prevent overfitting and
# improve generalization ability to unseen data e.g. the test-set.
new_model.add(Dropout(0.5))

# Add the final layer for the actual classification.
new_model.add(Dense(num_classes, activation='softmax'))
```

```
optimizer = Adam(lr=1e-5)
```

```
loss = 'categorical_crossentropy'
```

```
metrics = ['accuracy']
```

```
def print_layer_trainable(mod):
    for layer in mod.layers:
        print("{0}:\t{1}".format(layer.trainable, layer.name))
```

```
print_layer_trainable(conv_model)
```

```
True:   input_1
True:   block1_conv1
True:   block1_conv2
True:   block1_pool
True:   block2_conv1
True:   block2_conv2
True:   block2_pool
True:   block3_conv1
True:   block3_conv2
True:   block3_conv3
True:   block3_pool
True:   block4_conv1
True:   block4_conv2
True:   block4_conv3
True:   block4_pool
True:   block5_conv1
True:   block5_conv2
True:   block5_conv3
True:   block5_pool
```

```
for layer in conv_model.layers:
    layer.trainable = False
```

```
print_layer_trainable(model)
```

```
False:  input_1
False:  block1_conv1
False:  block1_conv2
False:  block1_pool
False:  block2_conv1
False:  block2_conv2
False:  block2_pool
False:  block3_conv1
False:  block3_conv2
False:  block3_conv3
False:  block3_pool
False:  block4_conv1
False:  block4_conv2
False:  block4_conv3
False:  block4_pool
False:  block5_conv1
False:  block5_conv2
False:  block5_conv3
False:  block5_pool
```

```
True:   flatten
True:   fc1
True:   fc2
True:   predictions
```

```
new_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
model (Functional)           (None, 7, 7, 512)         14714688
_________________________________________________________________
flatten (Flatten)            (None, 25088)             0
_________________________________________________________________
dense (Dense)                (None, 1024)              25691136
_________________________________________________________________
dropout (Dropout)            (None, 1024)              0
_________________________________________________________________
dense_1 (Dense)              (None, 10)                10250
=================================================================
Total params: 40,416,074
Trainable params: 25,701,386
Non-trainable params: 14,714,688
_________________________________________________________________
```

```
new_model.compile(optimizer=optimizer, loss=loss, metrics=metrics)
```

```
epochs = 30
steps_per_epoch = 1700/20
```

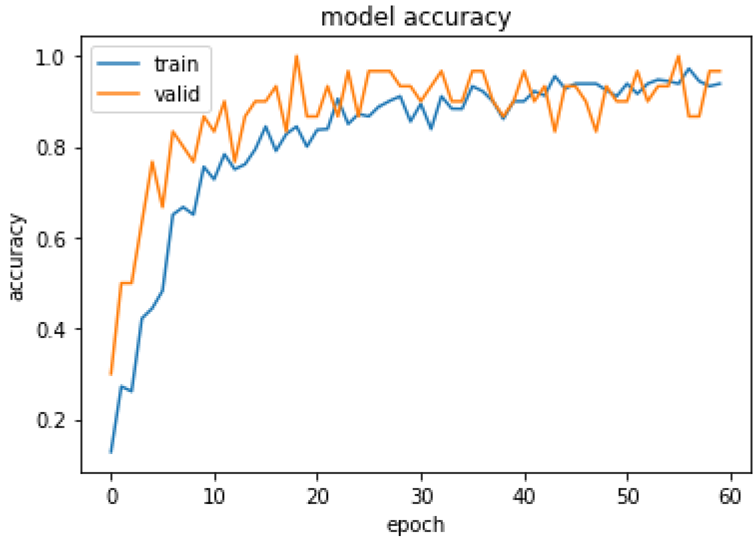
```
history = new_model.fit_generator(train_batches, steps_per_epoch=18,validation_data=valid_bat
```

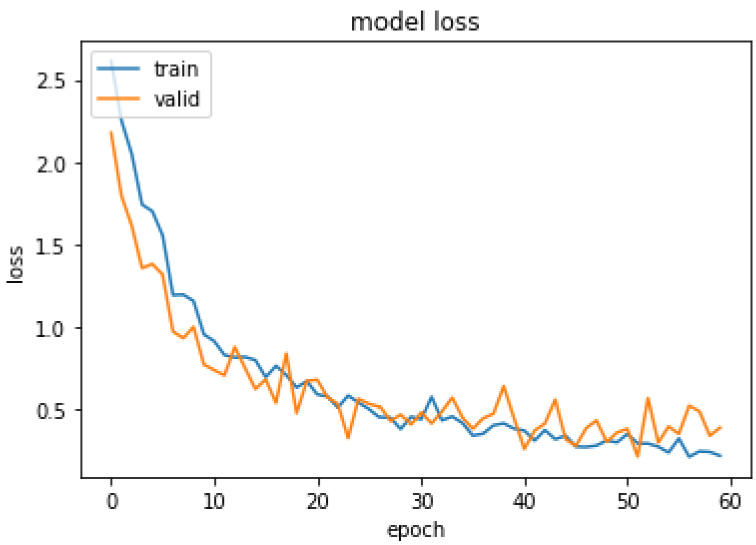
```
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:184
  warnings.warn('`Model.fit_generator` is deprecated and '
Epoch 1/60
18/18 - 34s - loss: 2.6142 - accuracy: 0.1278 - val_loss: 2.1772 - val_accuracy: 0.30
Epoch 2/60
18/18 - 1s - loss: 2.2524 - accuracy: 0.2722 - val_loss: 1.7951 - val_accuracy: 0.500
Epoch 3/60
18/18 - 1s - loss: 2.0489 - accuracy: 0.2611 - val_loss: 1.6127 - val_accuracy: 0.500
Epoch 4/60
18/18 - 1s - loss: 1.7414 - accuracy: 0.4222 - val_loss: 1.3553 - val_accuracy: 0.633
Epoch 5/60
18/18 - 1s - loss: 1.7007 - accuracy: 0.4444 - val_loss: 1.3797 - val_accuracy: 0.766
Epoch 6/60
18/18 - 1s - loss: 1.5533 - accuracy: 0.4833 - val_loss: 1.3156 - val_accuracy: 0.666
Epoch 7/60
18/18 - 1s - loss: 1.1943 - accuracy: 0.6500 - val_loss: 0.9729 - val_accuracy: 0.833
Epoch 8/60
18/18 - 1s - loss: 1.1970 - accuracy: 0.6667 - val_loss: 0.9321 - val_accuracy: 0.800
```

```
Epoch 9/60
18/18 - 1s - loss: 1.1578 - accuracy: 0.6500 - val_loss: 1.0007 - val_accuracy: 0.766
Epoch 10/60
18/18 - 1s - loss: 0.9552 - accuracy: 0.7556 - val_loss: 0.7718 - val_accuracy: 0.866
Epoch 11/60
18/18 - 2s - loss: 0.9141 - accuracy: 0.7278 - val_loss: 0.7382 - val_accuracy: 0.833
Epoch 12/60
18/18 - 2s - loss: 0.8294 - accuracy: 0.7833 - val_loss: 0.7067 - val_accuracy: 0.900
Epoch 13/60
18/18 - 2s - loss: 0.8154 - accuracy: 0.7500 - val_loss: 0.8783 - val_accuracy: 0.766
Epoch 14/60
18/18 - 1s - loss: 0.8180 - accuracy: 0.7611 - val_loss: 0.7504 - val_accuracy: 0.866
Epoch 15/60
18/18 - 1s - loss: 0.7987 - accuracy: 0.7944 - val_loss: 0.6229 - val_accuracy: 0.900
Epoch 16/60
18/18 - 1s - loss: 0.6944 - accuracy: 0.8444 - val_loss: 0.6816 - val_accuracy: 0.900
Epoch 17/60
18/18 - 1s - loss: 0.7644 - accuracy: 0.7907 - val_loss: 0.5387 - val_accuracy: 0.933
Epoch 18/60
18/18 - 1s - loss: 0.7076 - accuracy: 0.8278 - val_loss: 0.8390 - val_accuracy: 0.833
Epoch 19/60
18/18 - 1s - loss: 0.6327 - accuracy: 0.8444 - val_loss: 0.4762 - val_accuracy: 1.000
Epoch 20/60
18/18 - 1s - loss: 0.6708 - accuracy: 0.8000 - val_loss: 0.6725 - val_accuracy: 0.866
Epoch 21/60
18/18 - 1s - loss: 0.5904 - accuracy: 0.8372 - val_loss: 0.6795 - val_accuracy: 0.866
Epoch 22/60
18/18 - 1s - loss: 0.5777 - accuracy: 0.8389 - val_loss: 0.5733 - val_accuracy: 0.933
Epoch 23/60
18/18 - 1s - loss: 0.5101 - accuracy: 0.9056 - val_loss: 0.5329 - val_accuracy: 0.866
Epoch 24/60
18/18 - 1s - loss: 0.5834 - accuracy: 0.8500 - val_loss: 0.3244 - val_accuracy: 0.966
Epoch 25/60
18/18 - 1s - loss: 0.5410 - accuracy: 0.8722 - val_loss: 0.5632 - val_accuracy: 0.866
Epoch 26/60
18/18 - 2s - loss: 0.5021 - accuracy: 0.8667 - val_loss: 0.5339 - val_accuracy: 0.966
Epoch 27/60
18/18 - 1s - loss: 0.4519 - accuracy: 0.8889 - val_loss: 0.5155 - val_accuracy: 0.966
Epoch 28/60
18/18 - 1s - loss: 0.4490 - accuracy: 0.9012 - val_loss: 0.4288 - val_accuracy: 0.966
```

```
# summarize history for accuracy
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'valid'], loc='upper left')
plt.show()
# summarize history for loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
```

```
plt.xlabel('epoch')
plt.legend(['train', 'valid'], loc='upper left')
plt.show()
```






```
test_labels = test_batches.classes
predictions = new_model.predict_generator(test_batches, steps=5, verbose=0)
```

```
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:1905:
  warnings.warn('`Model.predict_generator` is deprecated and '
```

```
cm = confusion_matrix(test_labels, predictions.argmax(axis=1))
```

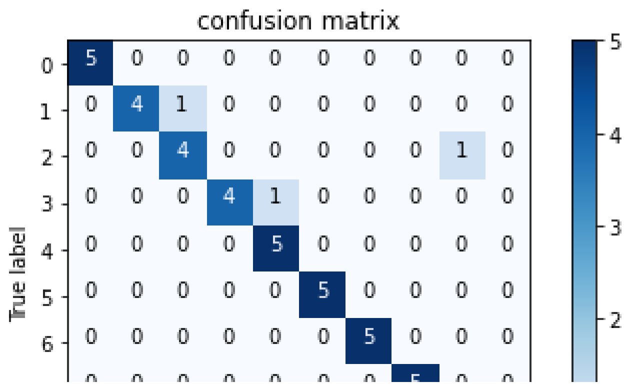
```
test_batches.class_indices
```

```
{'0': 0,
 '1': 1,
```

```
 '2': 2,
 '3': 3,
 '4': 4,
 '5': 5,
 '6': 6,
 '7': 7,
 '8': 8,
 '9': 9}
```

```
def plot_confusion_matrix(cm, classes,
                        normalize=False,
                        title='Confusion matrix',
                        cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    print(cm)

    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, 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')


cm_plot_labels = ['0','1','2','3','4','5','6','7','8','9']
plot_confusion_matrix(cm, cm_plot_labels, title='confusion matrix')
```

```
Confusion matrix, without normalization
[[5 0 0 0 0 0 0 0 0 0]
 [0 4 1 0 0 0 0 0 0 0]
 [0 0 4 0 0 0 0 0 1 0]
 [0 0 0 4 1 0 0 0 0 0]
 [0 0 0 0 5 0 0 0 0 0]
 [0 0 0 0 0 5 0 0 0 0]
 [0 0 0 0 0 0 5 0 0 0]
 [0 0 0 0 0 0 0 5 0 0]
 [0 0 0 0 0 0 0 0 4 1]
 [0 0 0 0 0 0 0 0 0 5]]
```




```
new_model.save('BD_VGG_model.h5')
```

predictions che dimensioni dovrebbe avere?? 50,10

```
predictions.shape
```

```
(50, 10)
```

training con aug dataset dopo che ha già imparato dal dataset non aumentato, la validation è molto buona inizialmente poichè su di essa non agiscoin i filtri di augmentation.

Il training su Augmented dataset è molto lento. Perchè?

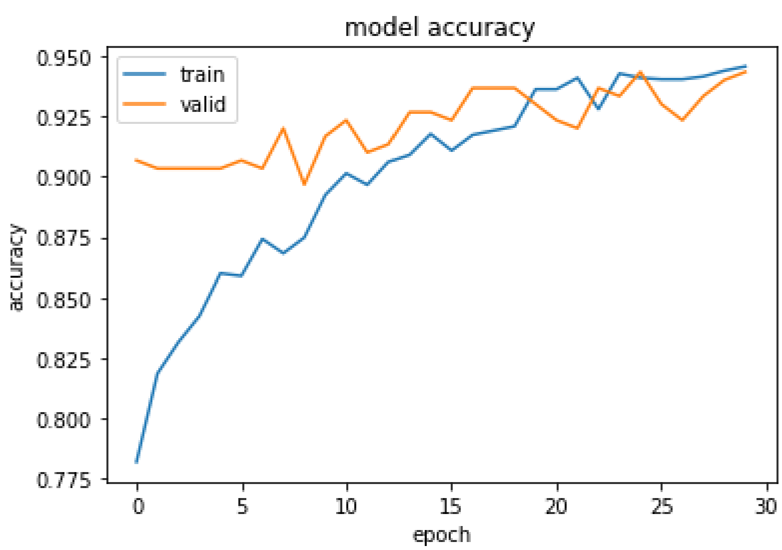
```
history = new_model.fit(x=generator_train,
                        epochs=epochs,
                        steps_per_epoch=steps_per_epoch,
                        verbose=2,
                        validation_data=generator_test,
                        validation_steps=steps_test)
```

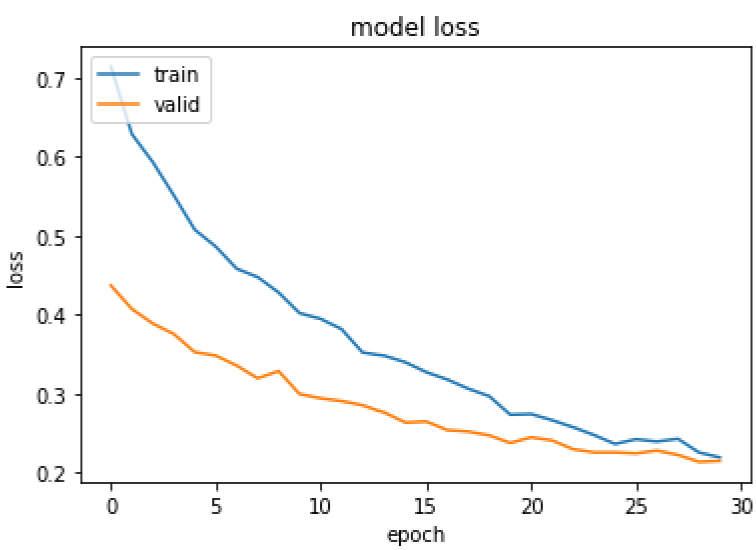
```
Epoch 1/30
85/85 - 34s - loss: 0.7143 - accuracy: 0.7819 - val_loss: 0.4370 - val_accuracy: 0.90
Epoch 2/30
85/85 - 28s - loss: 0.6287 - accuracy: 0.8186 - val_loss: 0.4073 - val_accuracy: 0.90
```

```
Epoch 3/30
85/85 - 29s - loss: 0.5932 - accuracy: 0.8316 - val_loss: 0.3889 - val_accuracy: 0.90
Epoch 4/30
85/85 - 28s - loss: 0.5512 - accuracy: 0.8424 - val_loss: 0.3756 - val_accuracy: 0.90
Epoch 5/30
85/85 - 28s - loss: 0.5077 - accuracy: 0.8599 - val_loss: 0.3527 - val_accuracy: 0.90
Epoch 6/30
85/85 - 28s - loss: 0.4863 - accuracy: 0.8588 - val_loss: 0.3483 - val_accuracy: 0.90
Epoch 7/30
85/85 - 28s - loss: 0.4583 - accuracy: 0.8741 - val_loss: 0.3357 - val_accuracy: 0.90
Epoch 8/30
85/85 - 28s - loss: 0.4477 - accuracy: 0.8682 - val_loss: 0.3196 - val_accuracy: 0.92
Epoch 9/30
85/85 - 28s - loss: 0.4282 - accuracy: 0.8747 - val_loss: 0.3287 - val_accuracy: 0.89
Epoch 10/30
85/85 - 28s - loss: 0.4020 - accuracy: 0.8924 - val_loss: 0.2997 - val_accuracy: 0.91
Epoch 11/30
85/85 - 28s - loss: 0.3949 - accuracy: 0.9013 - val_loss: 0.2943 - val_accuracy: 0.92
Epoch 12/30
85/85 - 27s - loss: 0.3819 - accuracy: 0.8966 - val_loss: 0.2908 - val_accuracy: 0.91
Epoch 13/30
85/85 - 29s - loss: 0.3523 - accuracy: 0.9060 - val_loss: 0.2855 - val_accuracy: 0.91
Epoch 14/30
85/85 - 28s - loss: 0.3481 - accuracy: 0.9090 - val_loss: 0.2762 - val_accuracy: 0.92
Epoch 15/30
85/85 - 28s - loss: 0.3399 - accuracy: 0.9176 - val_loss: 0.2636 - val_accuracy: 0.92
Epoch 16/30
85/85 - 27s - loss: 0.3273 - accuracy: 0.9108 - val_loss: 0.2648 - val_accuracy: 0.92
Epoch 17/30
85/85 - 27s - loss: 0.3180 - accuracy: 0.9173 - val_loss: 0.2540 - val_accuracy: 0.93
Epoch 18/30
85/85 - 28s - loss: 0.3064 - accuracy: 0.9190 - val_loss: 0.2521 - val_accuracy: 0.93
Epoch 19/30
85/85 - 28s - loss: 0.2969 - accuracy: 0.9208 - val_loss: 0.2473 - val_accuracy: 0.93
Epoch 20/30
85/85 - 28s - loss: 0.2736 - accuracy: 0.9362 - val_loss: 0.2377 - val_accuracy: 0.93
Epoch 21/30
85/85 - 28s - loss: 0.2743 - accuracy: 0.9362 - val_loss: 0.2449 - val_accuracy: 0.92
Epoch 22/30
85/85 - 27s - loss: 0.2665 - accuracy: 0.9409 - val_loss: 0.2409 - val_accuracy: 0.92
Epoch 23/30
85/85 - 27s - loss: 0.2577 - accuracy: 0.9279 - val_loss: 0.2298 - val_accuracy: 0.93
Epoch 24/30
85/85 - 27s - loss: 0.2477 - accuracy: 0.9427 - val_loss: 0.2258 - val_accuracy: 0.93
Epoch 25/30
85/85 - 27s - loss: 0.2364 - accuracy: 0.9409 - val_loss: 0.2258 - val_accuracy: 0.94
Epoch 26/30
85/85 - 27s - loss: 0.2424 - accuracy: 0.9403 - val_loss: 0.2245 - val_accuracy: 0.93
Epoch 27/30
85/85 - 28s - loss: 0.2395 - accuracy: 0.9403 - val_loss: 0.2281 - val_accuracy: 0.92
Epoch 28/30
85/85 - 28s - loss: 0.2430 - accuracy: 0.9415 - val_loss: 0.2226 - val_accuracy: 0.93
Epoch 29/30
85/85 - 27s - loss: 0.2257 - accuracy: 0.9439 - val_loss: 0.2138 - val_accuracy: 0.94
Epoch 30/30
```

```
# summarize history for accuracy
```

```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'valid'], loc='upper left')
plt.show()
# summarize history for loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'valid'], loc='upper left')
plt.show()
```





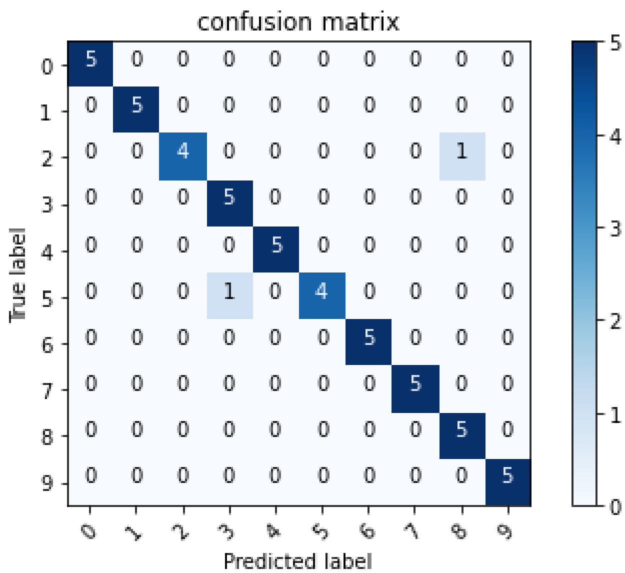

```
predictions = new_model.predict_generator(test_batches, steps=5, verbose=0)
```

```
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:1905:
  warnings.warn('`Model.predict_generator` is deprecated and '
```

```
cm = confusion_matrix(test_labels, predictions.argmax(axis=1))
```

```
cm_plot_labels = ['0','1','2','3','4','5','6','7','8','9']
plot_confusion_matrix(cm, cm_plot_labels, title='confusion matrix')
```

```
Confusion matrix, without normalization
[[5 0 0 0 0 0 0 0 0 0]
 [0 5 0 0 0 0 0 0 0 0]
 [0 0 4 0 0 0 0 0 1 0]
 [0 0 0 5 0 0 0 0 0 0]
 [0 0 0 0 5 0 0 0 0 0]
 [0 0 0 1 0 4 0 0 0 0]
 [0 0 0 0 0 0 5 0 0 0]
 [0 0 0 0 0 0 0 5 0 0]
 [0 0 0 0 0 0 0 0 5 0]
 [0 0 0 0 0 0 0 0 0 5]]
```




```
new_model.save('BD_AUG_VGG_model.h5')
```

Da test con webcam si trovano alcuni errori, allora procedo con un tuning dei due livelli superficiali del conv_model che non ho ancora trainato

```
for layer in conv_model.layers:
    # Boolean whether this layer is trainable.
    trainable = ('block5' in layer.name or 'block4' in layer.name)

    # Set the layer's bool.
    layer.trainable = trainable
```

```
print_layer_trainable(model)
```

```
False:  input_1
False:  block1_conv1
False:  block1_conv2
False:  block1_pool
False:  block2_conv1
False:  block2_conv2
False:  block2_pool
False:  block3_conv1
False:  block3_conv2
False:  block3_conv3
False:  block3_pool
True:   block4_conv1
True:   block4_conv2
True:   block4_conv3
True:   block4_pool
True:   block5_conv1
True:   block5_conv2
True:   block5_conv3
True:   block5_pool
True:   flatten
True:   fc1
True:   fc2
True:   predictions
```

la learning rate è meglio se è minore del caso precedente in modo da evitare eccessive variazioni dovute all'errore dei layers aggiunti da me

```
optimizer_fine = Adam(lr=1e-5)
```

```
fine_model = new_model
fine_model.compile(optimizer=optimizer_fine, loss=loss, metrics=metrics)
```

Oltra all'augmentation ci sono anche molti parametri da gestire

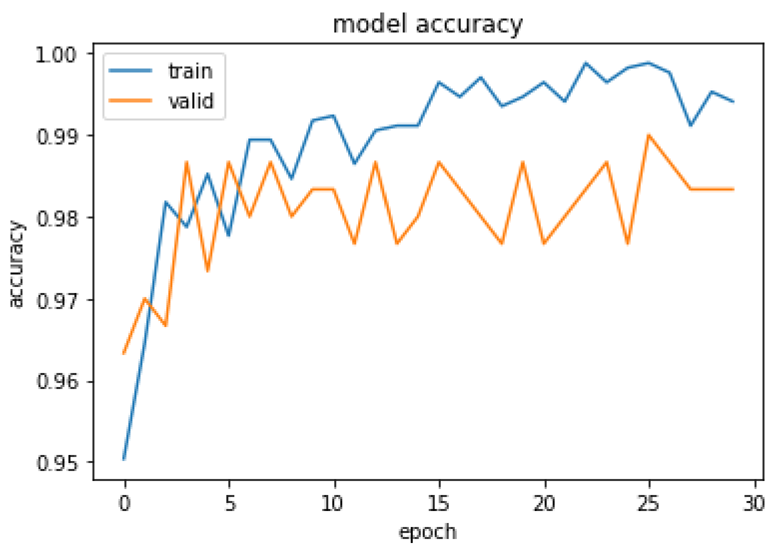
```
history = fine_model.fit(x=generator_train,
                         epochs=epochs,
                         steps_per_epoch=steps_per_epoch,
                         verbose=2,
                         validation_data=generator_test,
                         validation_steps=steps_test)
```

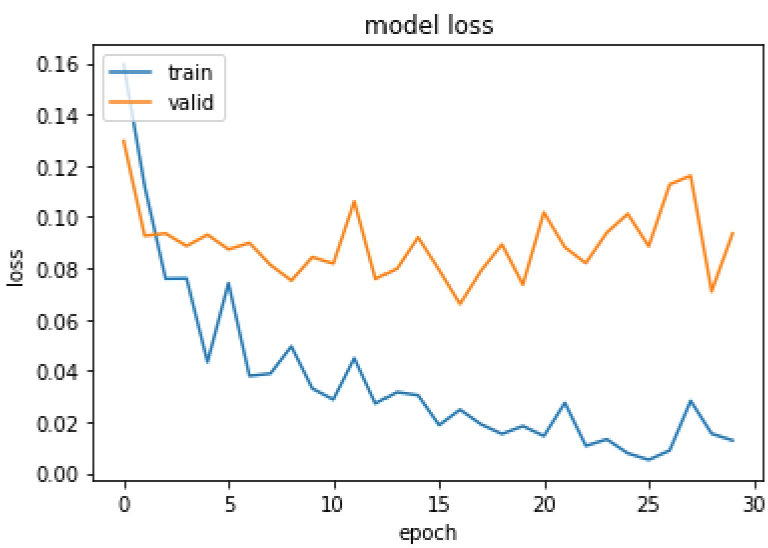
```
Epoch 1/30
85/85 - 29s - loss: 0.1594 - accuracy: 0.9504 - val_loss: 0.1296 - val_accuracy: 0.96
Epoch 2/30
85/85 - 28s - loss: 0.1120 - accuracy: 0.9645 - val_loss: 0.0926 - val_accuracy: 0.97
Epoch 3/30
85/85 - 28s - loss: 0.0759 - accuracy: 0.9818 - val_loss: 0.0935 - val_accuracy: 0.96
Epoch 4/30
85/85 - 28s - loss: 0.0760 - accuracy: 0.9787 - val_loss: 0.0886 - val_accuracy: 0.98
Epoch 5/30
```

```
85/85 - 28s - loss: 0.0433 - accuracy: 0.9852 - val_loss: 0.0930 - val_accuracy: 0.97
Epoch 6/30
85/85 - 28s - loss: 0.0742 - accuracy: 0.9776 - val_loss: 0.0873 - val_accuracy: 0.98
Epoch 7/30
85/85 - 28s - loss: 0.0379 - accuracy: 0.9894 - val_loss: 0.0898 - val_accuracy: 0.98
Epoch 8/30
85/85 - 28s - loss: 0.0388 - accuracy: 0.9894 - val_loss: 0.0812 - val_accuracy: 0.98
Epoch 9/30
85/85 - 28s - loss: 0.0495 - accuracy: 0.9846 - val_loss: 0.0752 - val_accuracy: 0.98
Epoch 10/30
85/85 - 28s - loss: 0.0330 - accuracy: 0.9918 - val_loss: 0.0843 - val_accuracy: 0.98
Epoch 11/30
85/85 - 28s - loss: 0.0287 - accuracy: 0.9924 - val_loss: 0.0817 - val_accuracy: 0.98
Epoch 12/30
85/85 - 28s - loss: 0.0449 - accuracy: 0.9865 - val_loss: 0.1060 - val_accuracy: 0.97
Epoch 13/30
85/85 - 28s - loss: 0.0272 - accuracy: 0.9905 - val_loss: 0.0758 - val_accuracy: 0.98
Epoch 14/30
85/85 - 28s - loss: 0.0316 - accuracy: 0.9911 - val_loss: 0.0797 - val_accuracy: 0.97
Epoch 15/30
85/85 - 28s - loss: 0.0304 - accuracy: 0.9911 - val_loss: 0.0920 - val_accuracy: 0.98
Epoch 16/30
85/85 - 28s - loss: 0.0187 - accuracy: 0.9965 - val_loss: 0.0793 - val_accuracy: 0.98
Epoch 17/30
85/85 - 28s - loss: 0.0248 - accuracy: 0.9947 - val_loss: 0.0660 - val_accuracy: 0.98
Epoch 18/30
85/85 - 28s - loss: 0.0191 - accuracy: 0.9971 - val_loss: 0.0789 - val_accuracy: 0.98
Epoch 19/30
85/85 - 28s - loss: 0.0153 - accuracy: 0.9935 - val_loss: 0.0892 - val_accuracy: 0.97
Epoch 20/30
85/85 - 28s - loss: 0.0184 - accuracy: 0.9947 - val_loss: 0.0735 - val_accuracy: 0.98
Epoch 21/30
85/85 - 28s - loss: 0.0145 - accuracy: 0.9965 - val_loss: 0.1017 - val_accuracy: 0.97
Epoch 22/30
85/85 - 28s - loss: 0.0275 - accuracy: 0.9941 - val_loss: 0.0881 - val_accuracy: 0.98
Epoch 23/30
85/85 - 28s - loss: 0.0106 - accuracy: 0.9988 - val_loss: 0.0819 - val_accuracy: 0.98
Epoch 24/30
85/85 - 28s - loss: 0.0132 - accuracy: 0.9965 - val_loss: 0.0938 - val_accuracy: 0.98
Epoch 25/30
85/85 - 28s - loss: 0.0078 - accuracy: 0.9982 - val_loss: 0.1011 - val_accuracy: 0.97
Epoch 26/30
85/85 - 28s - loss: 0.0052 - accuracy: 0.9988 - val_loss: 0.0885 - val_accuracy: 0.99
Epoch 27/30
85/85 - 28s - loss: 0.0089 - accuracy: 0.9976 - val_loss: 0.1126 - val_accuracy: 0.98
Epoch 28/30
85/85 - 30s - loss: 0.0282 - accuracy: 0.9911 - val_loss: 0.1160 - val_accuracy: 0.98
Epoch 29/30
85/85 - 29s - loss: 0.0154 - accuracy: 0.9953 - val_loss: 0.0709 - val_accuracy: 0.98
Epoch 30/30
```

```
# summarize history for accuracy
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
```

```
plt.legend(['train', 'valid'], loc='upper left')
plt.show()
# summarize history for loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'valid'], loc='upper left')
plt.show()
```






```
fine_predictions = fine_model.predict_generator(test_batches, steps=5, verbose=0)
```

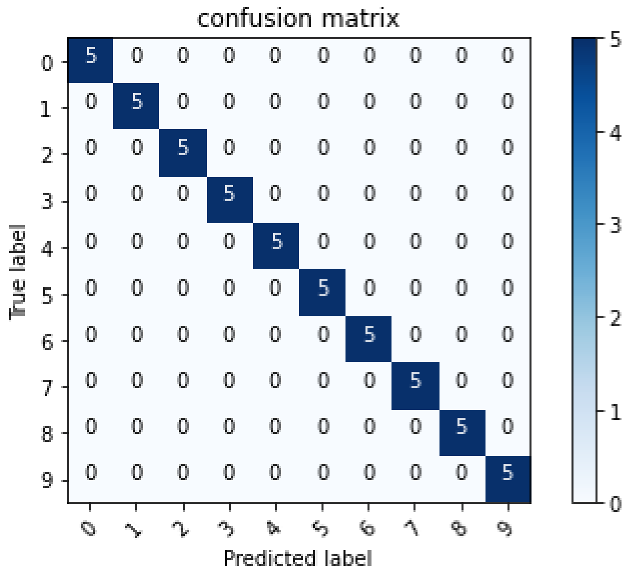
```
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:1905:
  warnings.warn('`Model.predict_generator` is deprecated and '
```

```
cm = confusion_matrix(test_labels, fine_predictions.argmax(axis=1))
```

```
cm_plot_labels = ['0','1','2','3','4','5','6','7','8','9']
```

```
cm_plot_labels = ['0','1','2','3','4','5','6','7','8','9']
plot_confusion_matrix(cm, cm_plot_labels, title='confusion matrix')
```

```
Confusion matrix, without normalization
[[5 0 0 0 0 0 0 0 0 0]
 [0 5 0 0 0 0 0 0 0 0]
 [0 0 5 0 0 0 0 0 0 0]
 [0 0 0 5 0 0 0 0 0 0]
 [0 0 0 0 5 0 0 0 0 0]
 [0 0 0 0 0 5 0 0 0 0]
 [0 0 0 0 0 0 5 0 0 0]
 [0 0 0 0 0 0 0 5 0 0]
 [0 0 0 0 0 0 0 0 5 0]
 [0 0 0 0 0 0 0 0 0 5]]
```




```
fine_model.save('BDVGG16_AUGdeeper_training.h5')
```