hw3

December 31, 2023

1 HOMEWORK 2 batch version

[ ]:
```
#%history -f output.txt
```

2 Libraries importation

[ ]:
```
import os
import cv2
import scipy
import numpy as np
import tensorflow as tf
from PIL import Image
from collections import defaultdict
from matplotlib import pyplot as plt
from sklearn.utils.class_weight import compute_class_weight
from tensorflow import keras
from keras.regularizers import l2
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Dense, Flatten,␣
↪Dropout, BatchNormalization
from tensorflow.keras.metrics import Precision, Recall, BinaryAccuracy
from tensorflow.keras.optimizers import Adam, SGD
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.preprocessing.image import ImageDataGenerator

print('libraries imported')
```

```
2023-12-31 11:02:07.959014: I tensorflow/core/util/port.cc:113] oneDNN custom
operations are on. You may see slightly different numerical results due to
floating-point round-off errors from different computation orders. To turn them
off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2023-12-31 11:02:07.960804: I external/local_tsl/tsl/cuda/cudart_stub.cc:31]
Could not find cuda drivers on your machine, GPU will not be used.
2023-12-31 11:02:07.988295: E
external/local_xla/xla/stream_executor/cuda/cuda_dnn.cc:9261] Unable to register
cuDNN factory: Attempting to register factory for plugin cuDNN when one has
already been registered
```

```
2023-12-31 11:02:07.988322: E
external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:607] Unable to register
cuFFT factory: Attempting to register factory for plugin cuFFT when one has
already been registered
2023-12-31 11:02:07.989062: E
external/local_xla/xla/stream_executor/cuda/cuda_blas.cc:1515] Unable to
register cuBLAS factory: Attempting to register factory for plugin cuBLAS when
one has already been registered
2023-12-31 11:02:07.993567: I external/local_tsl/tsl/cuda/cudart_stub.cc:31]
Could not find cuda drivers on your machine, GPU will not be used.
2023-12-31 11:02:07.994175: I tensorflow/core/platform/cpu_feature_guard.cc:182]
This TensorFlow binary is optimized to use available CPU instructions in
performance-critical operations.
To enable the following instructions: AVX2 AVX512F AVX512_VNNI FMA, in other
operations, rebuild TensorFlow with the appropriate compiler flags.
2023-12-31 11:02:08.585995: W
tensorflow/compiler/tf2tensorrt/utils/py_utils.cc:38] TF-TRT Warning: Could not
find TensorRT
```

```
libraries imported
```

3 settings

[ ]:
```
# Avoid OOM errors by setting GPU memory consumption growth
gpus = tf.config.experimental.list_physical_devices('GPU')
for gpu in gpus:
    tf.config.experimental.set_memory_growth(gpu, True)
```

4 Data Collection

4.1 Data Augmentation

[ ]:
```
datagen_train = ImageDataGenerator(
    rotation_range=40,
    width_shift_range=0.15,
    height_shift_range=0.15,
    shear_range=0.2,
    zoom_range=0,
    horizontal_flip=False,
    vertical_flip=False,
    rescale=1./96,
    validation_split=0.2
)

datagen_val = ImageDataGenerator(
    rescale=1./96,
    validation_split=0.2,
```

```
    horizontal_flip=False,
    vertical_flip=False,
)

datagen = ImageDataGenerator(
    rotation_range=40,
    width_shift_range=0.15,
    height_shift_range=0.15,
    shear_range=0.2,
    zoom_range=0,
    horizontal_flip=False,
    rescale=1./96,
    fill_mode='nearest',
)

datablanket = ImageDataGenerator(
    rescale=1./96,
)
```

[ ]:
```
Train = datablanket.flow_from_directory(
    'train',
    target_size=(96,96),
    batch_size=32,
    class_mode='categorical',
    subset='training'
)

Val = datablanket.flow_from_directory(
    'train',
    target_size=(96,96),
    batch_size=32,
    class_mode='categorical',
    subset = 'validation',
)

train_labels = []
train_labels = Train.classes
num_classes = Train.num_classes
train_labels_one_hot = tf.keras.utils.to_categorical(train_labels,
 ↪num_classes=num_classes)
```

```
Found 6369 images belonging to 5 classes.
Found 0 images belonging to 5 classes.
```

4.2 Data Load

4.2.1 Load without validation

[ ]:
```
Train = datagen.flow_from_directory(
    'train',
    target_size=(96,96),
    batch_size=32,
    class_mode='categorical'
)

train_labels = []
train_labels = Train.classes
num_classes = Train.num_classes
train_labels_one_hot = tf.keras.utils.to_categorical(train_labels,␣
↪num_classes=num_classes)
```

4.2.2 Load with validation

[ ]:
```
Train = datagen_train.flow_from_directory(
    'train',
    target_size=(96,96),
    batch_size=32,
    class_mode='categorical',
    subset='training'
)

Val = datagen_val.flow_from_directory(
    'train',
    target_size=(96,96),
    batch_size=32,
    class_mode='categorical',
    subset='validation'
)

train_labels = []
train_labels = Train.classes
num_classes = Train.num_classes
train_labels_one_hot = tf.keras.utils.to_categorical(train_labels,␣
↪num_classes=num_classes)
```

4.3 Visualization of the dataset

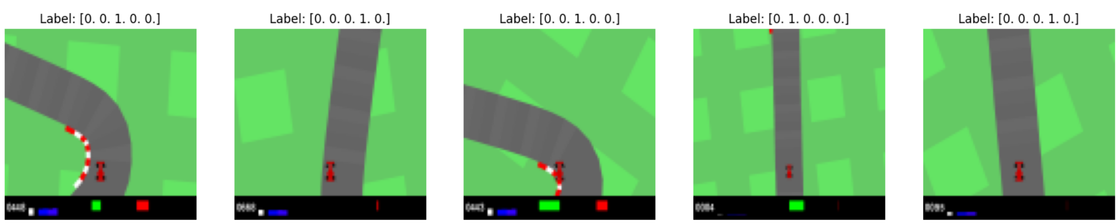
[ ]:
```
def visualize_dataset(dataset, num_samples=5):
    for images, labels in dataset:
        num_samples_batch = min(num_samples, len(images))
        fig, ax = plt.subplots(1, num_samples_batch, figsize=(20, 20))
```

```
        for i in range(num_samples_batch):
            ax[i].imshow((images[i] * 96).astype("uint8"))  # Remove the rescaling here
            ax[i].set_title(f"Label: {labels[i]}")
            ax[i].axis("off")

        plt.show()
        break


# num_samples = 5
# for images, labels in Train.take(1):
#     num_samples_batch = min(num_samples, len(images))
#     fig, ax = plt.subplots(1, num_samples_batch, figsize=(20, 20))
#     for i in range(num_samples):
#         ax[i].imshow(images[i].numpy().astype("uint8"))
#         ax[i].set_title(f"Label: {labels[i]}")
#         ax[i].axis("off")
#     plt.show()
```

[ ]:
```
visualize_dataset(Train)
```



5 Data Preprocessing

- Resize images to a common size (e.g., 96x96, as mentioned in the description).
- Normalize pixel values to a range between 0 and 1.
- Consider data augmentation techniques (e.g., rotation, flipping) to increase the diversity of your training set.

6 Model Selection:

6.1 Model Design

- Define your own CNN architecture. Start with a simple architecture and gradually increase complexity if needed.
- Experiment with different layer configurations, activation functions, and filter sizes.
- Consider incorporating dropout for regularization.

6.2 Approach 1

- First Architecture aims to be narrow and deep
- Choose appropriate hyperparameters (learning rate, batch size, etc.).

[ ]:
```
model = Sequential()
```

[ ]:
```
# Layers
# (3,3) is the pixel selection, 1 is the translation of pixels
model.add(Conv2D(32, (3,3), activation='relu', input_shape=(256,256,3)))
model.add(MaxPooling2D())
model.add(Dropout(0.25))

model.add(Conv2D(64, (3,3), activation='relu'))
model.add(MaxPooling2D())
model.add(Dropout(0.25))

model.add(Conv2D(128, (3,3), activation='relu'))
model.add(MaxPooling2D())
model.add(Dropout(0.25))

model.add(Flatten())

model.add(Dense(512, activation='relu'))
model.add(Dropout(0.5)) # Dropout layer to reduce overfitting

num_classes = 5
model.add(Dense(num_classes, activation='softmax'))
```

[ ]:
```
optimizer = Adam(learning_rate=0.001)
```

Validation ON

[ ]:
```
metrics = ['accuracy', 'val_accuracy']
```

Validation OFF

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

[ ]:
```
model.compile(optimizer, loss=tf._losses.CategoricalCrossentropy(),
 ↪metrics=metrics)
```

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

6.3 Approach 2

- Second architecture aims to be wider and less deep
- Adjust hyperparameters independently of the first approach.

[ ]:

```
# model = Sequential()

# # feature learning
# model.add(Conv2D(96, (3, 3), strides=(1, 1), activation='relu',␣
↪input_shape=(96, 96, 3)))
# model.add(MaxPooling2D((2, 2), strides=(1, 1)))
# model.add(BatchNormalization())

# model.add(Conv2D(256, (3, 3), strides=(1, 1), activation='relu'))
# model.add(MaxPooling2D((2, 2), strides=(1, 1)))
# model.add(BatchNormalization())

# model.add(Conv2D(384, (3, 3), strides=(1, 1), activation='relu'))
# model.add(MaxPooling2D((2, 2), strides=(1, 1)))
# model.add(BatchNormalization())

# # classification
# model.add(Flatten())

# model.add(Dense(4096, activation='relu', kernel_regularizer=l2(0.0001)))
# model.add(Dropout(0.4))
# model.add(BatchNormalization())

# num_classes = 5
# model.add(Dense(num_classes, activation='softmax'))

model = Sequential()

# Feature learning
model.add(Conv2D(32, 3, activation='relu', input_shape=(96, 96, 3)))
model.add(MaxPooling2D(2, 2))
model.add(BatchNormalization())
model.add(Dropout(0.05))

model.add(Conv2D(64, 3, activation='relu', kernel_regularizer=l2(0.001)))
model.add(MaxPooling2D(2, 2))
model.add(BatchNormalization())
model.add(Dropout(0.1))

model.add(Conv2D(64, 3, activation='relu', kernel_regularizer=l2(0.001)))
model.add(MaxPooling2D(2, 2))
model.add(BatchNormalization())
model.add(Dropout(0.2))

model.add(Conv2D(128, 3, activation='relu', kernel_regularizer=l2(0.001)))
model.add(MaxPooling2D(2, 2))
model.add(Dropout(0.3))
```

```
model.add(Conv2D(1256, 3, activation='relu', kernel_regularizer=l2(0.001)))
model.add(MaxPooling2D(2, 2))
model.add(Dropout(0.4))

# classification
model.add(Flatten())

model.add(Dense(512, activation='relu', kernel_regularizer=l2(0.001)))
model.add(Dropout(0.5))

num_classes = 5
model.add(Dense(num_classes, activation='softmax'))
```

Optimizer Adam

[ ]:
```
beta_1 = 0.9
beta_2 = 0.999
optimizer = Adam(learning_rate=0.0001, beta_1=beta_1, beta_2=beta_2)
loss = keras.losses.CategoricalCrossentropy()
```

Optimizer SGD

[ ]:
```
optimizer=SGD(learning_rate=0.01, momentum=0.9)
```

Validation ON

[ ]:
```
model.compile(optimizer=optimizer, loss=loss, metrics=['accuracy'])

for layer in model.layers:
    print(f"{layer.name}: Input shape - {layer.input_shape}")
```

```
conv2d: Input shape - (None, 96, 96, 3)
max_pooling2d: Input shape - (None, 94, 94, 32)
batch_normalization: Input shape - (None, 47, 47, 32)
dropout: Input shape - (None, 47, 47, 32)
conv2d_1: Input shape - (None, 47, 47, 32)
max_pooling2d_1: Input shape - (None, 45, 45, 64)
batch_normalization_1: Input shape - (None, 22, 22, 64)
dropout_1: Input shape - (None, 22, 22, 64)
conv2d_2: Input shape - (None, 22, 22, 64)
max_pooling2d_2: Input shape - (None, 20, 20, 64)
batch_normalization_2: Input shape - (None, 10, 10, 64)
dropout_2: Input shape - (None, 10, 10, 64)
conv2d_3: Input shape - (None, 10, 10, 64)
max_pooling2d_3: Input shape - (None, 8, 8, 128)
dropout_3: Input shape - (None, 4, 4, 128)
conv2d_4: Input shape - (None, 4, 4, 128)
```

```
max_pooling2d_4: Input shape - (None, 2, 2, 1256)
dropout_4: Input shape - (None, 1, 1, 1256)
flatten: Input shape - (None, 1, 1, 1256)
dense: Input shape - (None, 1256)
dropout_5: Input shape - (None, 512)
dense_1: Input shape - (None, 512)
```

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

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 94, 94, 32)        896

 max_pooling2d (MaxPooling2  (None, 47, 47, 32)        0
 D)

 batch_normalization (Batch  (None, 47, 47, 32)        128
 Normalization)

 dropout (Dropout)           (None, 47, 47, 32)        0

 conv2d_1 (Conv2D)           (None, 45, 45, 64)        18496

 max_pooling2d_1 (MaxPoolin  (None, 22, 22, 64)        0
 g2D)

 batch_normalization_1 (Bat  (None, 22, 22, 64)        256
 chNormalization)

 dropout_1 (Dropout)         (None, 22, 22, 64)        0

 conv2d_2 (Conv2D)           (None, 20, 20, 64)        36928

 max_pooling2d_2 (MaxPoolin  (None, 10, 10, 64)        0
 g2D)

 batch_normalization_2 (Bat  (None, 10, 10, 64)        256
 chNormalization)

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 94, 94, 32)        896

 max_pooling2d (MaxPooling2  (None, 47, 47, 32)        0
 D)
```

```
batch_normalization (Batch  (None, 47, 47, 32)        128
Normalization)

dropout (Dropout)           (None, 47, 47, 32)        0

conv2d_1 (Conv2D)           (None, 45, 45, 64)        18496

max_pooling2d_1 (MaxPoolin  (None, 22, 22, 64)        0
g2D)

batch_normalization_1 (Bat  (None, 22, 22, 64)        256
chNormalization)

dropout_1 (Dropout)         (None, 22, 22, 64)        0

conv2d_2 (Conv2D)           (None, 20, 20, 64)        36928

max_pooling2d_2 (MaxPoolin  (None, 10, 10, 64)        0
g2D)

batch_normalization_2 (Bat  (None, 10, 10, 64)        256
chNormalization)

dropout_2 (Dropout)         (None, 10, 10, 64)        0

conv2d_3 (Conv2D)           (None, 8, 8, 128)         73856

max_pooling2d_3 (MaxPoolin  (None, 4, 4, 128)         0
g2D)

dropout_3 (Dropout)         (None, 4, 4, 128)         0

conv2d_4 (Conv2D)           (None, 2, 2, 1256)        1448168

max_pooling2d_4 (MaxPoolin  (None, 1, 1, 1256)        0
g2D)

dropout_4 (Dropout)         (None, 1, 1, 1256)        0

flatten (Flatten)           (None, 1256)              0

dense (Dense)               (None, 512)               643584

dropout_5 (Dropout)         (None, 512)               0

dense_1 (Dense)             (None, 5)                 2565
```

```
=================================================================
Total params: 2225133 (8.49 MB)
Trainable params: 2224813 (8.49 MB)
Non-trainable params: 320 (1.25 KB)
_________________________________________________________________
```

Validation OFF

```
[ ]: model.compile(optimizer, loss=tf._losses.CategoricalCrossentropy(),␣
     ↪metrics=['accuracy'])

     model.summary()
     for layer in model.layers:
         print(layer.output_shape)
```

6.4 Hyperparameter Analysis

- Choose at least one hyperparameter (e.g., learning rate) and perform a systematic analysis.
- Train models with different values of the chosen hyperparameter.
- Compare and visualize the impact on metrics.
- Consider to apply an early stopping of the training in order to avoid overfitting (see slide 11 pag 55)
- Consider if to apply Dropout or parameter sharing

7 Model Training

```
[ ]: logdir = 'logs'
     tensorboard_callback = tf.keras.callbacks.TensorBoard(log_dir=logdir)
```

```
[ ]: class_labels = np.unique(train_labels)
     class_weights = compute_class_weight(class_weight='balanced', classes=np.
     ↪unique(train_labels), y=train_labels)
     class_weights_dict = dict(zip(class_labels, class_weights))
```

7.0.1 Fitting with early stopping

validation OFF

```
[ ]: early_stopping = EarlyStopping(monitor='val_loss', patience=5,␣
     ↪restore_best_weights=True)
     hist = model.fit(Train, epochs=20, callbacks=[tensorboard_callback,␣
     ↪early_stopping], class_weight=class_weights_dict)
```

validation ON

```
[ ]: early_stopping = EarlyStopping(
         monitor='val_loss',
         patience=5,
```

```
    restore_best_weights=True)

hist = model.fit(
    Train,
    epochs=20,
    callbacks=[tensorboard_callback, early_stopping],
    validation_data=Val,
    validation_steps=Val.samples // Val.batch_size,
    class_weight=class_weights_dict)
```

```
Epoch 1/20
200/200 [==============================] - ETA: 0s - loss: 2.7256 - accuracy:
0.3321WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which
is not available. Available metrics are: loss,accuracy
200/200 [==============================] - 21s 98ms/step - loss: 2.7256 -
accuracy: 0.3321
Epoch 2/20
200/200 [==============================] - ETA: 0s - loss: 2.5263 - accuracy:
0.4390WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which
is not available. Available metrics are: loss,accuracy
200/200 [==============================] - 20s 101ms/step - loss: 2.5263 -
accuracy: 0.4390
Epoch 3/20
200/200 [==============================] - ETA: 0s - loss: 2.4687 - accuracy:
0.4538WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which
is not available. Available metrics are: loss,accuracy
200/200 [==============================] - 20s 100ms/step - loss: 2.4687 -
accuracy: 0.4538
Epoch 4/20
200/200 [==============================] - ETA: 0s - loss: 2.3982 - accuracy:
0.4753WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which
is not available. Available metrics are: loss,accuracy
200/200 [==============================] - 20s 100ms/step - loss: 2.3982 -
accuracy: 0.4753
Epoch 5/20
200/200 [==============================] - ETA: 0s - loss: 2.3260 - accuracy:
0.4903WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which
is not available. Available metrics are: loss,accuracy
200/200 [==============================] - 20s 101ms/step - loss: 2.3260 -
accuracy: 0.4903
Epoch 6/20
200/200 [==============================] - ETA: 0s - loss: 2.2766 - accuracy:
0.5012WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which
is not available. Available metrics are: loss,accuracy
200/200 [==============================] - 20s 101ms/step - loss: 2.2766 -
accuracy: 0.5012
Epoch 7/20
```

```
200/200 [==============================] - ETA: 0s - loss: 2.2358 - accuracy:
0.5064WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which
is not available. Available metrics are: loss,accuracy
200/200 [==============================] - 20s 102ms/step - loss: 2.2358 -
accuracy: 0.5064
Epoch 8/20
200/200 [==============================] - ETA: 0s - loss: 2.1849 - accuracy:
0.5158WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which
is not available. Available metrics are: loss,accuracy
200/200 [==============================] - 21s 104ms/step - loss: 2.1849 -
accuracy: 0.5158
Epoch 9/20
200/200 [==============================] - ETA: 0s - loss: 2.1493 - accuracy:
0.5233WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which
is not available. Available metrics are: loss,accuracy
200/200 [==============================] - 20s 102ms/step - loss: 2.1493 -
accuracy: 0.5233
Epoch 10/20
200/200 [==============================] - ETA: 0s - loss: 2.1077 - accuracy:
0.5367WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which
is not available. Available metrics are: loss,accuracy
200/200 [==============================] - 21s 104ms/step - loss: 2.1077 -
accuracy: 0.5367
Epoch 11/20
200/200 [==============================] - ETA: 0s - loss: 2.0559 - accuracy:
0.5516WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which
is not available. Available metrics are: loss,accuracy
200/200 [==============================] - 21s 103ms/step - loss: 2.0559 -
accuracy: 0.5516
Epoch 12/20
200/200 [==============================] - ETA: 0s - loss: 2.0191 - accuracy:
0.5494WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which
is not available. Available metrics are: loss,accuracy
200/200 [==============================] - 21s 105ms/step - loss: 2.0191 -
accuracy: 0.5494
Epoch 13/20
200/200 [==============================] - ETA: 0s - loss: 1.9867 - accuracy:
0.5458WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which
is not available. Available metrics are: loss,accuracy
200/200 [==============================] - 20s 101ms/step - loss: 1.9867 -
accuracy: 0.5458
Epoch 14/20
200/200 [==============================] - ETA: 0s - loss: 1.9427 - accuracy:
0.5577WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which
is not available. Available metrics are: loss,accuracy
200/200 [==============================] - 20s 101ms/step - loss: 1.9427 -
accuracy: 0.5577
Epoch 15/20
```

```
200/200 [==============================] - ETA: 0s - loss: 1.9167 - accuracy:
0.5602WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which
is not available. Available metrics are: loss,accuracy
200/200 [==============================] - 20s 101ms/step - loss: 1.9167 -
accuracy: 0.5602
Epoch 16/20
200/200 [==============================] - ETA: 0s - loss: 1.8843 - accuracy:
0.5654WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which
is not available. Available metrics are: loss,accuracy
200/200 [==============================] - 20s 102ms/step - loss: 1.8843 -
accuracy: 0.5654
Epoch 17/20
200/200 [==============================] - ETA: 0s - loss: 1.8503 - accuracy:
0.5549WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which
is not available. Available metrics are: loss,accuracy
200/200 [==============================] - 21s 103ms/step - loss: 1.8503 -
accuracy: 0.5549
Epoch 18/20
200/200 [==============================] - ETA: 0s - loss: 1.8332 - accuracy:
0.5670WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which
is not available. Available metrics are: loss,accuracy
200/200 [==============================] - 22s 112ms/step - loss: 1.8332 -
accuracy: 0.5670
Epoch 19/20
200/200 [==============================] - ETA: 0s - loss: 1.7973 - accuracy:
0.5596WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which
is not available. Available metrics are: loss,accuracy
200/200 [==============================] - 24s 120ms/step - loss: 1.7973 -
accuracy: 0.5596
Epoch 20/20
200/200 [==============================] - ETA: 0s - loss: 1.7498 - accuracy:
0.5797WARNING:tensorflow:Early stopping conditioned on metric `val_loss` which
is not available. Available metrics are: loss,accuracy
200/200 [==============================] - 22s 111ms/step - loss: 1.7498 -
accuracy: 0.5797
```

7.0.2 Fitting without early stopping

Validation OFF

[ ]:
```
hist = model.fit(Train, epochs=20, callbacks=[tensorboard_callback],
    class_weight=class_weights_dict)
```

Validation ON

[ ]:
```
hist = model.fit(Train, epochs=20, callbacks=[tensorboard_callback],
    validation_data=Val, class_weight=class_weights_dict)
```

7.1 Plotting Model Performance

7.1.1 Validation ON

[ ]:
```
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15, 5))

ax1.plot(hist.history['loss'], color='teal', label='train_loss')
ax1.plot(hist.history['val_loss'], color='orange', label='val_loss')  #␣
 ↪Validation loss
ax1.set_title('Loss')
ax1.legend()

ax2.plot(hist.history['accuracy'], color='teal', label='train_accuracy')
ax2.plot(hist.history['val_accuracy'], color='orange', label='val_accuracy')  #␣
 ↪Validation accuracy
ax2.set_title('Accuracy')
ax2.legend()

plt.show()
```

7.1.2 Validation OFF

[ ]:
```
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15, 5))

ax1.plot(hist.history['loss'], color='teal', label='train_loss')
ax1.set_title('Loss')
ax1.legend()

ax2.plot(hist.history['accuracy'], color='teal', label='train_accuracy')
ax2.set_title('Accuracy')
ax2.legend()

plt.show()
```

8 Test

[ ]:
```
Test = tf.keras.utils.image_dataset_from_directory('test')
test_iterator = Test.as_numpy_iterator()

all_X_test = []
all_y_test = []

for test_batch in test_iterator:
    X_test_batch, y_test_batch = test_batch
    X_test_normalized_batch = X_test_batch/96.0
    yhat_batch = model.predict(X_test_normalized_batch)
    all_X_test.append(X_test_normalized_batch)
```

```
    all_y_test.append(y_test_batch)

X_test_normalized = np.concatenate(all_X_test)
y_test = np.concatenate(all_y_test)

test_iterator = Test.as_numpy_iterator()
Test_batch = next(test_iterator)
X_test, y_test = Test_batch
X_test_normalized = X_test/96.0
```

[ ]:
```
yhat = model.predict(X_test_normalized)
```

[ ]:
```
pre = Precision()
re = Recall()
acc = BinaryAccuracy()
```

[ ]:
```
for batch in Test.as_numpy_iterator():
    X, y = batch
    yhat = model.predict(X)
    y_one_hot = tf.keras.utils.to_categorical(y, num_classes=num_classes)
    pre.update_state(y_one_hot, yhat)
    re.update_state(y_one_hot, yhat)
    acc.update_state(y_one_hot, yhat)
```

[ ]:
```
print(f'Precision:{pre.result().numpy()}, Recall:{re.result().numpy()},␣
↪Accuracy:{acc.result().numpy()}')
```

9 Results Visualization and Comparison

- Create visualizations (tables, charts, graphs) to present your results.
- Provide detailed commentary on each visualization, explaining trends or differences observed.

9.1 Comparison on accuracy between methods

9.1.1 On train and validation

[ ]:
```
fig = plt.figure(figsize=(16, 8))
plt.plot(hist.history['accuracy'], color='teal', label='train_accuracy')
plt.plot(hist.history['val_accuracy'], color='orange', label='val_accuracy')
plt.suptitle('Model accuracy comparison on train and validation', fontsize=14)
plt.legend(loc="upper left")
plt.show()
```

9.1.2 On Test

[ ]:
```
fig=plt.figure(figsize=(16, 8))
fig = plt.figure(figsize=(16, 8))
plt.plot(acc.result, color='teal', label='test_accuracy') # to edit
plt.suptitle('Model accuracy comparison on test', fontsize=14)
plt.legend(loc="upper left")
plt.show()
```

9.2 Fine-Tuning

9.3 Deployment

[ ]:
```

```

##valutazioni da fare poi: - regularization per ridurre l'overfitting? - il numero di images cambia da classe a classe (train) vedere se serve prenderne un numero uguale per ciascuna classe -