

# hw2

December 27, 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
from tensorflow.keras.preprocessing.image import ImageDataGenerator

print('libraries imported')
```

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 = ImageDataGenerator(  
    rotation_range=0,  
    width_shift_range=0,  
    height_shift_range=0,  
    shear_range=0,  
    zoom_range=0,  
    horizontal_flip=True,  
    rescale=1./255  
)
```

### 4.2 Data Load

```
[ ]: Train = datagen.flow_from_directory(  
    'train',  
    target_size=(256,256),  
    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)
```

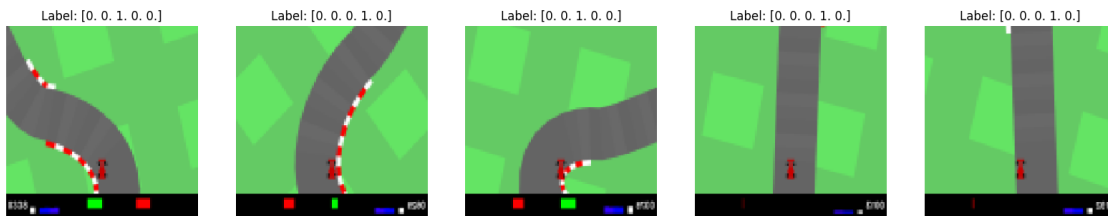
Found 6369 images belonging to 5 classes.

### 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] * 255).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

- Define the first approach with a specific architecture, optimizer, and regularization techniques.
- Choose appropriate hyperparameters (learning rate, batch size, etc.).
- Train the model on the training set and evaluate on the test set.
- Collect and analyze metrics such as accuracy, precision, recall, and F1 score.

```
[ ]: 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)
```

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

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

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 254, 254, 32)	896
max_pooling2d (MaxPooling2D)	(None, 127, 127, 32)	0
dropout (Dropout)	(None, 127, 127, 32)	0
conv2d_1 (Conv2D)	(None, 125, 125, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 62, 62, 64)	0
dropout_1 (Dropout)	(None, 62, 62, 64)	0

conv2d_2 (Conv2D)	(None, 60, 60, 128)	73856
max_pooling2d_2 (MaxPooling2D)	(None, 30, 30, 128)	0
dropout_2 (Dropout)	(None, 30, 30, 128)	0
flatten (Flatten)	(None, 115200)	0
dense (Dense)	(None, 512)	58982912
-----		
Layer (type)	Output Shape	Param #
=====		
conv2d (Conv2D)	(None, 254, 254, 32)	896
max_pooling2d (MaxPooling2D)	(None, 127, 127, 32)	0
dropout (Dropout)	(None, 127, 127, 32)	0
conv2d_1 (Conv2D)	(None, 125, 125, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 62, 62, 64)	0
dropout_1 (Dropout)	(None, 62, 62, 64)	0
conv2d_2 (Conv2D)	(None, 60, 60, 128)	73856
max_pooling2d_2 (MaxPooling2D)	(None, 30, 30, 128)	0
dropout_2 (Dropout)	(None, 30, 30, 128)	0
flatten (Flatten)	(None, 115200)	0
dense (Dense)	(None, 512)	58982912
dropout_3 (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 5)	2565
=====		
Total params: 59078725 (225.37 MB)		
Trainable params: 59078725 (225.37 MB)		
Non-trainable params: 0 (0.00 Byte)		
-----		

### 6.3 Approach 2

- Define the second approach with a different architecture, optimizer, or regularization techniques.
- Adjust hyperparameters independently of the first approach.
- Train the model on the training set and evaluate on the test set.
- Collect and analyze metrics as done for the first approach.

```
[ ]: model = keras.models.Sequential([
    keras.layers.Flatten(input_shape=(256, 256, 3)),
    keras.layers.Dense(64, activation='relu', kernel_regularizer=keras.
↳regularizers.l2(0.001)),
    keras.layers.Dense(32, activation='relu', kernel_regularizer=keras.
↳regularizers.l2(0.001)),
    keras.layers.Dense(num_classes, activation='softmax')
])
```

```
[ ]: beta_1 = 0.9
    beta_2 = 0.999
    optimizer = Adam(learning_rate=0.01, beta_1=beta_1, beta_2=beta_2)
```

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

```
[ ]: model.summary
```

```
[ ]: <bound method Model.summary of <keras.src.engine.sequential.Sequential object at
0x7fee0b64a6e0>>
```

### 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)
```

without validation data:

```
[ ]: 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))
```

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

```
Epoch 1/20  
200/200 [=====] - 24s 119ms/step - loss: 60.9023 -  
accuracy: 0.1726  
Epoch 2/20  
200/200 [=====] - 23s 115ms/step - loss: 4.2770 -  
accuracy: 0.2068  
Epoch 3/20  
200/200 [=====] - 23s 113ms/step - loss: 2.3106 -  
accuracy: 0.1572  
Epoch 4/20  
200/200 [=====] - 23s 114ms/step - loss: 1.7657 -  
accuracy: 0.1696  
Epoch 5/20  
200/200 [=====] - 23s 114ms/step - loss: 1.6542 -  
accuracy: 0.1715  
Epoch 6/20  
200/200 [=====] - 23s 114ms/step - loss: 1.6322 -  
accuracy: 0.2407  
Epoch 7/20  
200/200 [=====] - 23s 115ms/step - loss: 2.6176 -  
accuracy: 0.2266  
Epoch 8/20  
200/200 [=====] - 23s 114ms/step - loss: 1.7754 -  
accuracy: 0.1449  
Epoch 9/20  
200/200 [=====] - 23s 115ms/step - loss: 2.0546 -  
accuracy: 0.1945  
Epoch 10/20  
200/200 [=====] - 23s 114ms/step - loss: 1.6540 -  
accuracy: 0.1735  
Epoch 11/20  
200/200 [=====] - 23s 115ms/step - loss: 1.6239 -  
accuracy: 0.2173  
Epoch 12/20  
200/200 [=====] - 23s 114ms/step - loss: 1.6225 -  
accuracy: 0.2402  
Epoch 13/20  
200/200 [=====] - 23s 114ms/step - loss: 1.6221 -  
accuracy: 0.1806  
Epoch 14/20  
200/200 [=====] - 23s 115ms/step - loss: 1.6451 -  
accuracy: 0.2140
```

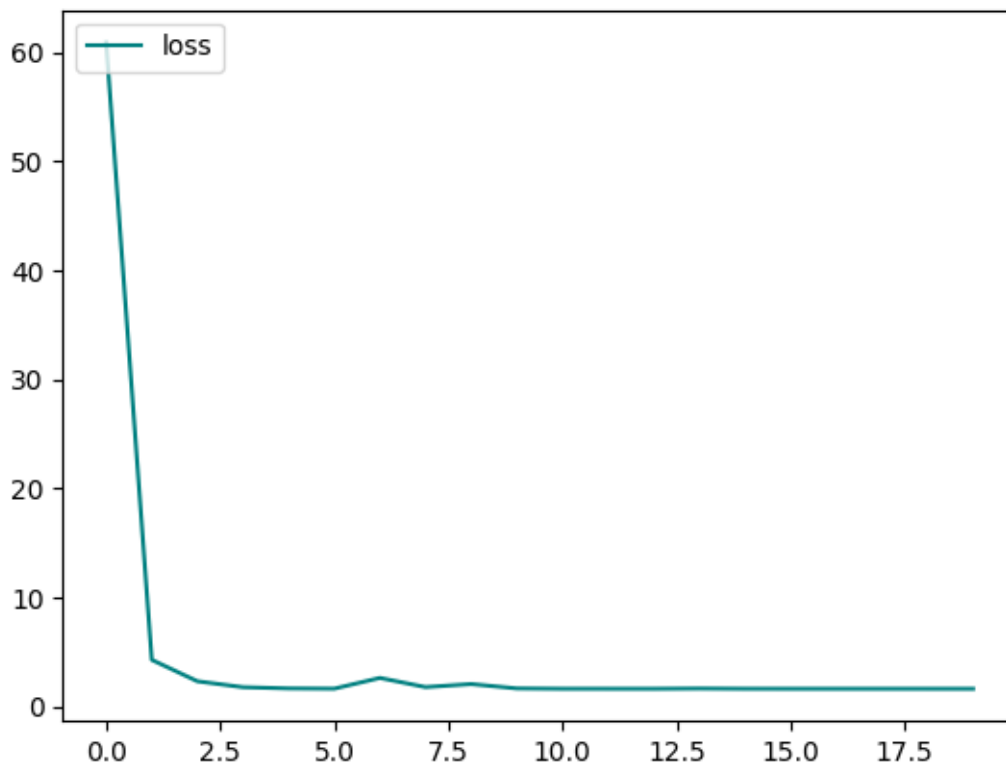
```
Epoch 15/20
200/200 [=====] - 23s 116ms/step - loss: 1.6249 -
accuracy: 0.2220
Epoch 16/20
200/200 [=====] - 23s 115ms/step - loss: 1.6219 -
accuracy: 0.2189
Epoch 17/20
200/200 [=====] - 23s 115ms/step - loss: 1.6219 -
accuracy: 0.2098
Epoch 18/20
200/200 [=====] - 23s 115ms/step - loss: 1.6222 -
accuracy: 0.1729
Epoch 19/20
200/200 [=====] - 23s 115ms/step - loss: 1.6215 -
accuracy: 0.2179
Epoch 20/20
200/200 [=====] - 23s 116ms/step - loss: 1.6215 -
accuracy: 0.1850
```

## 7.1 Plotting Model Performance

```
[ ]: fig = plt.figure()
plt.plot(hist.history['loss'], color='teal', label='loss')
fig.suptitle('Loss', fontsize=20)
plt.legend(loc="upper left")
plt.show()
```

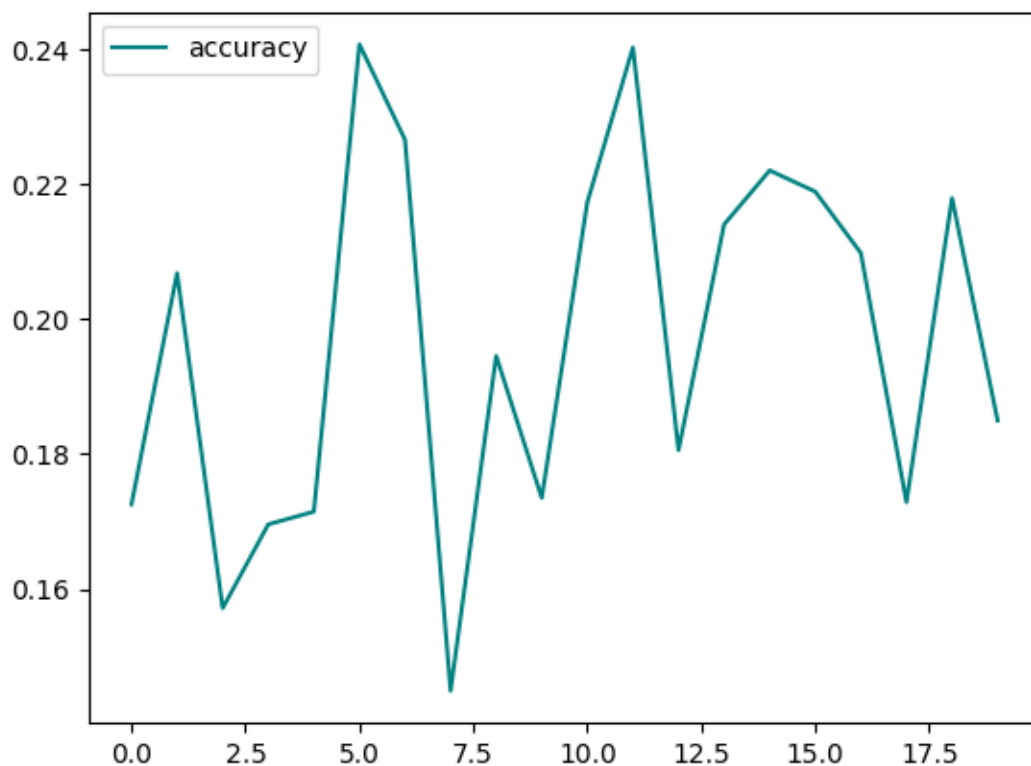


## Loss



```
[ ]: fig = plt.figure()
plt.plot(hist.history['accuracy'], color='teal', label='accuracy')
fig.suptitle('Accuracy', fontsize=20)
plt.legend(loc="upper left")
plt.show()
```

## Accuracy



## 8 Evaluate Performance

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

## 9 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/255.0  
         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/255.0

```

Found 2749 files belonging to 5 classes.

```

1/1 [=====] - 0s 35ms/step
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```
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1/1 [=====] - 0s 40ms/step
```

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

```
1/1 [=====] - 0s 28ms/step
1/1 [=====] - 0s 28ms/step
```

```
[ ]: 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)
```

```
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```

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```

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

Precision:0.0, Recall:0.0, Accuracy:0.800000011920929

## 10 Results Visualization and Comparison

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

### 10.1 Comparison on accuracy between methods

#### 10.1.1 On train

```
[ ]: fig=plt.figure(figsize=(16, 8))
    # insert comparison on accuracies

plt.suptitle('Model accuracy comparison on train', fontsize=14)
plt.show()
```

#### 10.1.2 On Test

```
[ ]: fig=plt.figure(figsize=(16, 8))
    # insert comparison on accuracies

plt.suptitle('Model accuracy comparison on test', fontsize=14)
plt.show()
```

### 10.2 Fine-Tuning

### 10.3 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 -