

# CNN-FFA-20E-15L-03

March 24, 2021

## 1 Are Relations Relevant in CNNs? *A Study Based on a Facial Dataset*

### 1.1 CNN with Features Further Apart (*20 Epochs - 15 Layers*)

#### 1.1.1 Imports, Seed, GPU integration

```
[1]: import numpy as np
import random
import tensorflow as tf
```

```
[2]: # Seeds for better reproducibility
seed = 42
np.random.seed(seed)
random.seed(seed)
tf.random.set_seed(seed)
```

```
[3]: from tensorflow.keras.layers import Dropout, Conv2D, BatchNormalization,
↳MaxPool2D, Dense, Flatten
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.python.keras.models import Sequential
from sklearn.metrics import confusion_matrix
import itertools
import matplotlib.pyplot as plt
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
%matplotlib inline
```

```
[4]: physical_devices = tf.config.experimental.list_physical_devices('GPU')
print("Num GPUs Available: ", len(physical_devices))
tf.config.experimental.set_memory_growth(physical_devices[0], True)
```

Num GPUs Available: 1

### 1.1.2 Data preparation

```
[5]: train_path = '../..//picasso_dataset/FFA-data/middle/train'
    valid_path = '../..//picasso_dataset/FFA-data/middle/valid'
    test_path = '../..//picasso_dataset/FFA-data/middle/test'

[6]: train_batches = ImageDataGenerator(preprocessing_function=tf.keras.applications.
    ↪vgg16.preprocess_input) \
    .flow_from_directory(directory=train_path, target_size=(224,224),
    ↪classes=['no_face', 'face'], batch_size=20)

    valid_batches = ImageDataGenerator(preprocessing_function=tf.keras.applications.
    ↪vgg16.preprocess_input) \
    .flow_from_directory(directory=valid_path, target_size=(224,224),
    ↪classes=['no_face', 'face'], batch_size=10)

    test_batches = ImageDataGenerator(preprocessing_function=tf.keras.applications.
    ↪vgg16.preprocess_input) \
    .flow_from_directory(directory=test_path, target_size=(224,224),
    ↪classes=['no_face', 'face'], batch_size=10, shuffle=False)
```

Found 16002 images belonging to 2 classes.

Found 998 images belonging to 2 classes.

Found 3000 images belonging to 2 classes.

```
[7]: assert train_batches.n == 16002
    assert valid_batches.n == 998
    assert test_batches.n == 3000
    assert train_batches.num_classes == valid_batches.num_classes == test_batches.
    ↪num_classes == 2
```

### 1.1.3 Building and training the CNN

```
[8]: dropout_rate=0.2

[9]: model = Sequential(name = "CNN-FFA")

    model.add(Conv2D(filters=32, kernel_size=(3, 3), activation='relu', padding =
    ↪'same', input_shape=(224,224,3), name = "Conv_1"))
    model.add(MaxPool2D(pool_size=(2, 2), name = "Max_1"))
    model.add(Dropout(rate=dropout_rate, name = "DO_1"))
    model.add(BatchNormalization(name = "BN_1"))

    model.add(Conv2D(filters=64, kernel_size=(3, 3), activation='relu', padding =
    ↪'same', name = "Conv_2"))
    model.add(MaxPool2D(pool_size=(2, 2), name = "Max_2"))
```

```

model.add(Conv2D(filters=128, kernel_size=(3, 3), activation='relu', padding =
↳ 'same', name = "Conv_3"))
model.add(MaxPool2D(pool_size=(2, 2), name = "Max_3"))
model.add(Dropout(rate=dropout_rate, name = "DO_3"))

model.add(Conv2D(filters=256, kernel_size=(3, 3), activation='relu', padding =
↳ 'same', name = "Conv_4"))
model.add(MaxPool2D(pool_size=(2, 2), name = "Max_4"))

model.add(Conv2D(filters=512, kernel_size=(3, 3), activation='relu', padding =
↳ 'same', name = "Conv_5"))
model.add(MaxPool2D(pool_size=(2, 2), name = "Max_5"))

# Fully connected layer
model.add(Flatten(name = "Flat_con"))
model.add(Dense(units=2, activation='softmax', name = "D_con"))

model.summary()
untrained_weights = list(model.get_weights()[0][0][0][0])

```

Model: "CNN-FFA"

Layer (type)	Output Shape	Param #
Conv_1 (Conv2D)	(None, 224, 224, 32)	896
Max_1 (MaxPooling2D)	(None, 112, 112, 32)	0
DO_1 (Dropout)	(None, 112, 112, 32)	0
BN_1 (BatchNormalization)	(None, 112, 112, 32)	128
Conv_2 (Conv2D)	(None, 112, 112, 64)	18496
Max_2 (MaxPooling2D)	(None, 56, 56, 64)	0
Conv_3 (Conv2D)	(None, 56, 56, 128)	73856
Max_3 (MaxPooling2D)	(None, 28, 28, 128)	0
DO_3 (Dropout)	(None, 28, 28, 128)	0
Conv_4 (Conv2D)	(None, 28, 28, 256)	295168
Max_4 (MaxPooling2D)	(None, 14, 14, 256)	0
Conv_5 (Conv2D)	(None, 14, 14, 512)	1180160

```

-----
Max_5 (MaxPooling2D)          (None, 7, 7, 512)          0
-----
Flat_con (Flatten)            (None, 25088)              0
-----
D_con (Dense)                 (None, 2)                  50178
=====
Total params: 1,618,882
Trainable params: 1,618,818
Non-trainable params: 64
-----

```

```
[10]: model.compile(optimizer=Adam(learning_rate=0.0001),
                    loss='categorical_crossentropy',
                    metrics=['accuracy'] )
```

```
[11]: history = model.fit(x=train_batches,
                          steps_per_epoch=len(train_batches),
                          validation_data=valid_batches,
                          validation_steps=len(valid_batches),
                          epochs=20,
                          verbose=2 )
```

Epoch 1/20

WARNING:tensorflow:Callbacks method `on\_train\_batch\_end` is slow compared to the batch time (batch time: 0.0149s vs `on\_train\_batch\_end` time: 0.0242s). Check your callbacks.

801/801 - 51s - loss: 0.1640 - accuracy: 0.9181 - val\_loss: 0.0175 - val\_accuracy: 0.9920

Epoch 2/20

801/801 - 39s - loss: 0.0117 - accuracy: 0.9962 - val\_loss: 0.0037 - val\_accuracy: 0.9990

Epoch 3/20

801/801 - 42s - loss: 0.0039 - accuracy: 0.9991 - val\_loss: 0.0056 - val\_accuracy: 0.9970

Epoch 4/20

801/801 - 42s - loss: 0.0045 - accuracy: 0.9984 - val\_loss: 0.0061 - val\_accuracy: 0.9980

Epoch 5/20

801/801 - 43s - loss: 0.0029 - accuracy: 0.9990 - val\_loss: 5.9781e-04 - val\_accuracy: 1.0000

Epoch 6/20

801/801 - 45s - loss: 1.7710e-04 - accuracy: 1.0000 - val\_loss: 1.2826e-04 - val\_accuracy: 1.0000

Epoch 7/20

801/801 - 45s - loss: 6.4840e-05 - accuracy: 1.0000 - val\_loss: 2.7593e-04 - val\_accuracy: 1.0000

Epoch 8/20

```

801/801 - 44s - loss: 0.0036 - accuracy: 0.9989 - val_loss: 0.0025 -
val_accuracy: 0.9990
Epoch 9/20
801/801 - 44s - loss: 0.0017 - accuracy: 0.9995 - val_loss: 0.0026 -
val_accuracy: 0.9990
Epoch 10/20
801/801 - 45s - loss: 0.0015 - accuracy: 0.9994 - val_loss: 1.8372e-04 -
val_accuracy: 1.0000
Epoch 11/20
801/801 - 44s - loss: 5.2314e-05 - accuracy: 1.0000 - val_loss: 4.9772e-05 -
val_accuracy: 1.0000
Epoch 12/20
801/801 - 43s - loss: 6.0395e-05 - accuracy: 1.0000 - val_loss: 5.3398e-04 -
val_accuracy: 1.0000
Epoch 13/20
801/801 - 43s - loss: 0.0035 - accuracy: 0.9991 - val_loss: 6.7836e-05 -
val_accuracy: 1.0000
Epoch 14/20
801/801 - 43s - loss: 0.0016 - accuracy: 0.9995 - val_loss: 2.2944e-04 -
val_accuracy: 1.0000
Epoch 15/20
801/801 - 43s - loss: 3.4889e-05 - accuracy: 1.0000 - val_loss: 7.3740e-06 -
val_accuracy: 1.0000
Epoch 16/20
801/801 - 43s - loss: 7.6852e-06 - accuracy: 1.0000 - val_loss: 7.1750e-06 -
val_accuracy: 1.0000
Epoch 17/20
801/801 - 43s - loss: 8.2791e-04 - accuracy: 0.9996 - val_loss: 0.0025 -
val_accuracy: 0.9990
Epoch 18/20
801/801 - 43s - loss: 2.8208e-05 - accuracy: 1.0000 - val_loss: 1.8782e-05 -
val_accuracy: 1.0000
Epoch 19/20
801/801 - 43s - loss: 4.7530e-06 - accuracy: 1.0000 - val_loss: 9.3158e-06 -
val_accuracy: 1.0000
Epoch 20/20
801/801 - 43s - loss: 0.0024 - accuracy: 0.9993 - val_loss: 2.0295e-04 -
val_accuracy: 1.0000

```

#### 1.1.4 Saving the model

```
[12]: filename='models/CNN-FFA-20E-15L-03.h5'
```

```
[13]: model.save(filename)
      saved_weights = list(model.get_weights()[0][0][0][0])
```

### 1.1.5 Loading the saved model

```
[14]: loaded_model = load_model(filename)
loaded_weights = list(loaded_model.get_weights()[0][0][0][0])

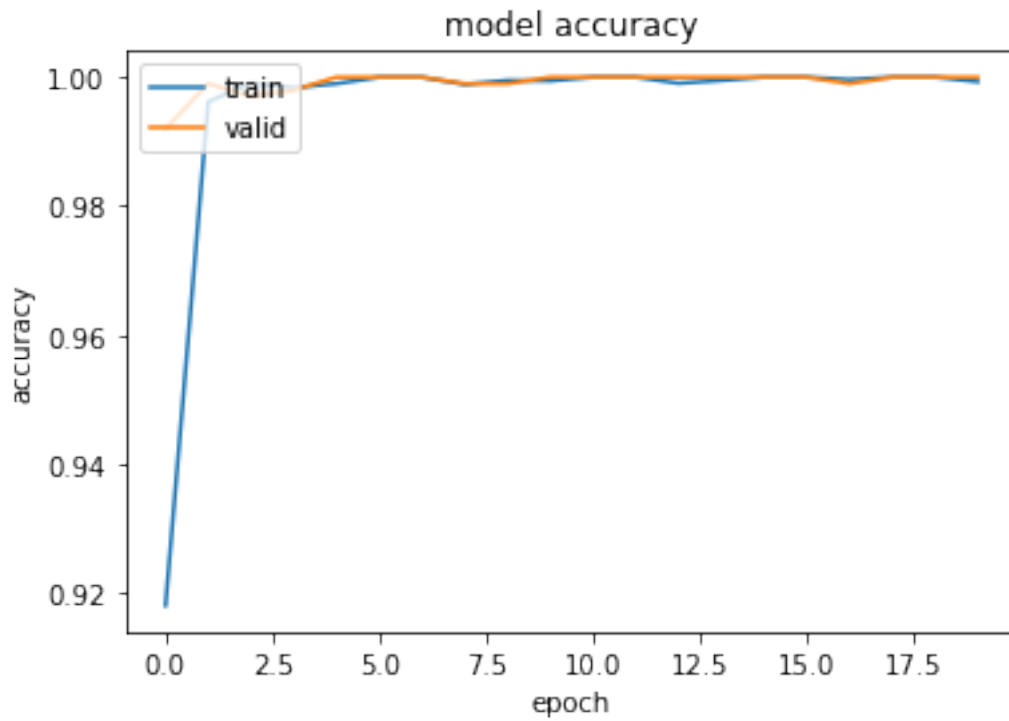
[15]: # Assertion that the model was saved and loaded successfully
assert untrained_weights != saved_weights
assert saved_weights == loaded_weights
```

### 1.1.6 Accuracy and loss of the trained model

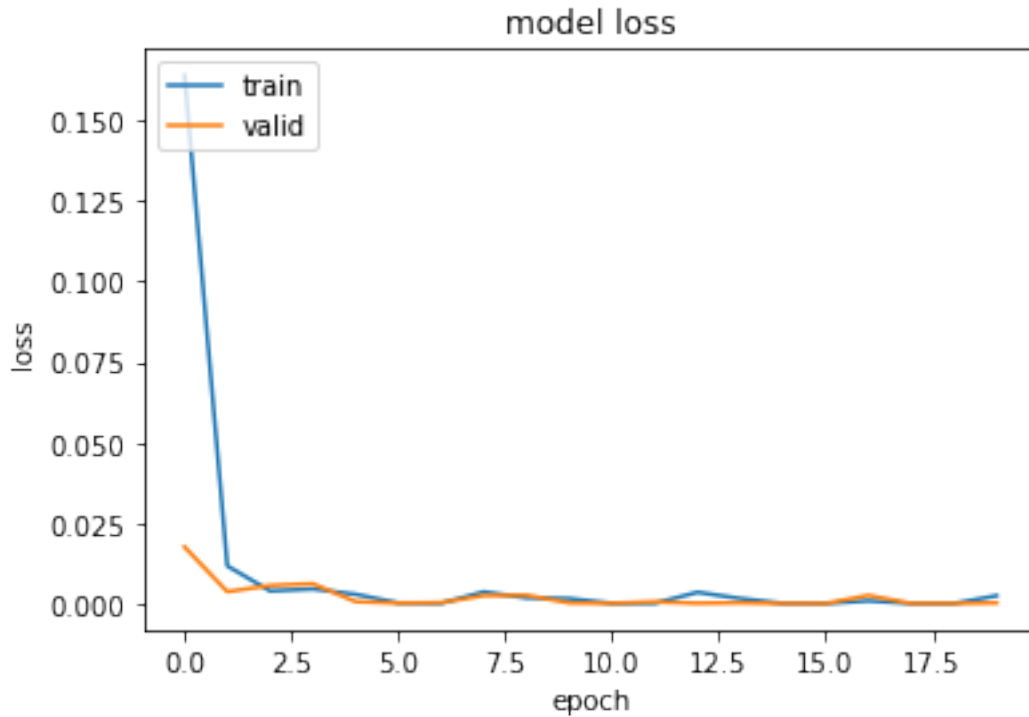
```
[16]: scores = loaded_model.evaluate(test_batches, verbose=2)
print("Accuracy: %.2f%%" % (scores[1]*100))
print("Loss: %.2f%%" % (scores[0]*100))
```

```
300/300 - 7s - loss: 2.0756e-04 - accuracy: 1.0000
Accuracy: 100.00%
Loss: 0.02%
```

```
[17]: #Course of 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()
```



```
[18]: #Course of 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()
```



### 1.1.7 Testing the CNN

```
[19]: predictions = loaded_model.predict(x=test_batches, steps=len(test_batches),
    ↪ verbose=0)
```

### 1.1.8 Index of wrongly predicted pictures

```
[20]: y_true=test_batches.classes
y_pred=np.argmax(predictions, axis=-1)
cm = confusion_matrix(y_true = y_true, y_pred = y_pred)
```

```
[21]: face_but_predicted_no_face=[]
no_face_but_predicted_face=[]

for i in range(len(predictions)):
    if y_true[i] != y_pred[i]:
        if y_true[i] == 1:
            face_but_predicted_no_face.append(i+8001-1500) #Index of file
    ↪ on disk
        else:
            no_face_but_predicted_face.append(i+8001) #Index of file on disk
```



```

print("Data from class 'face', that was wrongly predicted as 'no-face' [",
      ↪len(face_but_predicted_no_face), "] :")
print(face_but_predicted_no_face)
print("-----")
print("Data from class 'no-face', that was wrongly predicted as 'face' [",
      ↪len(no_face_but_predicted_face), "] :")
print(no_face_but_predicted_face)

```

Data from class 'face', that was wrongly predicted as 'no-face' [ 0 ] :

[]

-----

Data from class 'no-face', that was wrongly predicted as 'face' [ 0 ] :

[]

### 1.1.9 Confusion matrix

```

[22]: def plot_confusion_matrix(cm, classes,
                                normalize=False,
                                title='Confusion matrix',
                                cmap=plt.cm.Blues):

    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')

```

```
[23]: test_batches.class_indices
```

```
[23]: {'no_face': 0, 'face': 1}
```

```
[24]: cm_plot_labels = ['no_face', 'face']  
plot_confusion_matrix(cm=cm, classes=cm_plot_labels, title='Confusion Matrix')
```

Confusion matrix, without normalization

```
[[1500   0]  
 [   0 1500]]
```



```
[ ]:
```