

## Project Development Phase Sprint - II

Date	05 November 2022
Team ID	PNT2022TMID35901
Project Name	Natural Disasters Intensity Analysis And Classification Using Artificial Intelligence
Maximum Marks	4 Marks

### Building the CNN Model for Natural Disaster Classification, Training and Validating it, and Testing results

The screenshot displays the IBM Watson Studio interface. The top navigation bar includes the IBM Watson Studio logo, a search bar, and user information for Raakesh Kumar C's Account. The breadcrumb trail shows the project path: Projects / Natural Disaster Intensity Analys... / Disaster Classification. The main workspace contains a Jupyter notebook with a code cell. The code is for a model fitting and validation process, using Keras and TensorFlow. The output of the code is a detailed log showing the training progress over 15 epochs. The log includes the number of images processed, time per step, loss, accuracy, and validation loss and accuracy. The right sidebar shows the 'Data' panel with a file upload section and a list of files, including 'Cyclone\_Wildfi...ake\_Database.zip'.

IBM Watson Studio

Search in your workspaces

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Raakesh Kumar C's Account

Dallas

RK

Projects / Natural Disaster Intensity Analys... / Disaster Classification

File Edit View Insert Cell Kernel Help

Not Trusted | Python 3.9

In [27]: `#Model Fitting - training and validation`  
`history=model.fit_generator(x_train,steps_per_epoch=len(x_train),epochs=20,validation_data=x_val,validation_steps=len(x_val))`  
`#steps_per_epoch = no of train images/batch size`  
`#validation_steps = no of test images/batch size`

Epoch 1/20  
310/310 [=====] - 384s 1s/step - loss: 1.1158 - accuracy: 0.5341 - val\_loss: 1.0172 - val\_accuracy: 0.6244  
Epoch 2/20  
310/310 [=====] - 380s 1s/step - loss: 0.7026 - accuracy: 0.7391 - val\_loss: 0.6189 - val\_accuracy: 0.7862  
Epoch 3/20  
310/310 [=====] - 378s 1s/step - loss: 0.6090 - accuracy: 0.7785 - val\_loss: 0.5414 - val\_accuracy: 0.8032  
Epoch 4/20  
310/310 [=====] - 378s 1s/step - loss: 0.5252 - accuracy: 0.8082 - val\_loss: 0.5541 - val\_accuracy: 0.8133  
Epoch 5/20  
310/310 [=====] - 375s 1s/step - loss: 0.4850 - accuracy: 0.8205 - val\_loss: 0.5834 - val\_accuracy: 0.7805  
Epoch 6/20  
310/310 [=====] - 376s 1s/step - loss: 0.4537 - accuracy: 0.8305 - val\_loss: 0.4234 - val\_accuracy: 0.8450  
Epoch 7/20  
310/310 [=====] - 378s 1s/step - loss: 0.4294 - accuracy: 0.8437 - val\_loss: 0.4307 - val\_accuracy: 0.8529  
Epoch 8/20  
310/310 [=====] - 379s 1s/step - loss: 0.4033 - accuracy: 0.8524 - val\_loss: 0.3810 - val\_accuracy: 0.8767  
Epoch 9/20  
310/310 [=====] - 379s 1s/step - loss: 0.3695 - accuracy: 0.8631 - val\_loss: 0.3842 - val\_accuracy: 0.8586  
Epoch 10/20  
310/310 [=====] - 383s 1s/step - loss: 0.3419 - accuracy: 0.8760 - val\_loss: 0.3953 - val\_accuracy: 0.8620  
Epoch 11/20  
310/310 [=====] - 380s 1s/step - loss: 0.3305 - accuracy: 0.8728 - val\_loss: 0.4521 - val\_accuracy: 0.8541  
Epoch 12/20  
310/310 [=====] - 383s 1s/step - loss: 0.3426 - accuracy: 0.8731 - val\_loss: 0.4412 - val\_accuracy: 0.8529  
Epoch 13/20  
310/310 [=====] - 378s 1s/step - loss: 0.3359 - accuracy: 0.8763 - val\_loss: 0.4537 - val\_accuracy: 0.8541  
Epoch 14/20  
310/310 [=====] - 384s 1s/step - loss: 0.3157 - accuracy: 0.8834 - val\_loss: 0.4474 - val\_accuracy: 0.8439  
Epoch 15/20  
310/310 [=====] - 380s 1s/step - loss: 0.2992 - accuracy: 0.8967 - val\_loss: 0.5975 - val\_accuracy: 0.8213

Data

Files

Connections

Upload one file at a time. All file types accepted. 5 GB max file size.

Drag and drop files here or upload.

Cyclone\_Wildfi...ake\_Database.zip

Insert to code

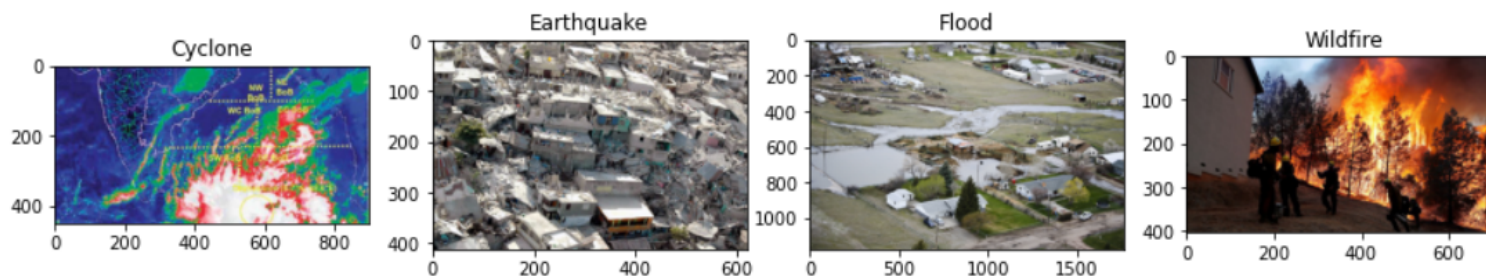
## 1. Indexing Disaster Classes

```
In [19]: #Classes of Disasters  
x_train.class_indices
```

```
Out[19]: {'Cyclone': 0, 'Earthquake': 1, 'Flood': 2, 'Wildfire': 3}
```

## 2. Sample Plot for each of the Classes

```
In [20]: #Sample Plot for each of the Classes  
from skimage import io  
f=['/home/wsuser/work/dataset/train/Cyclone/1.jpg', '/home/wsuser/work/dataset/train/Earthquake/0.jpg', '/home/wsuser/work/dataset/train/Flood/0.jpg', '/home/wsuser/work/dataset/train/Wildfire/0.jpg']  
class_names=['Cyclone', 'Earthquake', 'Flood', 'Wildfire']  
x, axarr = plt.subplots(1,4,figsize=(15,15))  
for i in range(4):  
    axarr[i].imshow(io.imread(f[i]))  
    axarr[i].title.set_text(class_names[i])
```



### 3. CNN Model Architecture

```
In [21]: model=Sequential()
```

```
In [22]: #Input Convolution Layer
model.add(Convolution2D(32,kernel_size=(3,3),input_shape=(299,299,3),strides=(1,1),activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
#Convolution Layer 2
model.add(Convolution2D(64,kernel_size=(3,3),input_shape=(299,299,3),strides=(1,1),activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.3))
#Convolution Layer 3
model.add(Convolution2D(32,kernel_size=(3,3),input_shape=(299,299,3),strides=(1,1),activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.3))
#Flattening of Output
model.add(Flatten())
#FCN or Dense Layer
model.add(Dense(units=256,kernel_initializer="random_uniform",activation="relu"))
model.add(Dropout(0.4))
#Output Layer
model.add(Dense(units=4,activation="softmax"))
```

### 4. Summary of the Model

```
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 297, 297, 32)	896
max_pooling2d (MaxPooling2D)	(None, 148, 148, 32)	0
conv2d_1 (Conv2D)	(None, 146, 146, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 73, 73, 64)	0
dropout (Dropout)	(None, 73, 73, 64)	0
conv2d_2 (Conv2D)	(None, 71, 71, 32)	18464
max_pooling2d_2 (MaxPooling2D)	(None, 35, 35, 32)	0
dropout_1 (Dropout)	(None, 35, 35, 32)	0
flatten (Flatten)	(None, 39200)	0
dense (Dense)	(None, 256)	10035456
dropout_2 (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 4)	1028

=====  
Total params: 10,074,340

Trainable params: 10,074,340

## 5. Compiling the Model

```
In [24]: #Compiling the Model
model.compile(loss="categorical_crossentropy", optimizer="adam", metrics=["accuracy"])
```

## 6. Training and Validating the Model

```
In [27]: #Model Fitting - training and validation
history=model.fit_generator(x_train,steps_per_epoch=len(x_train),epochs=20,validation_data=x_val,validation_steps=len(x_val),
#steps_per_epoch = no of train images/batch size
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Epoch 1/20
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```

---

```

Epoch 11/20
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curacy: 0.8541
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curacy: 0.8439
Epoch 15/20
310/310 [=====] - 380s 1s/step - loss: 0.2992 - accuracy: 0.8967 - val_loss: 0.5975 - val_ac
curacy: 0.8213
Epoch 16/20
310/310 [=====] - 380s 1s/step - loss: 0.2774 - accuracy: 0.8999 - val_loss: 0.4088 - val_ac
curacy: 0.8597
Epoch 17/20
310/310 [=====] - 384s 1s/step - loss: 0.2534 - accuracy: 0.9109 - val_loss: 0.3894 - val_ac
curacy: 0.8643
Epoch 18/20
310/310 [=====] - 379s 1s/step - loss: 0.2779 - accuracy: 0.9015 - val_loss: 0.4040 - val_ac
curacy: 0.8665
Epoch 19/20
310/310 [=====] - 379s 1s/step - loss: 0.2430 - accuracy: 0.9093 - val_loss: 0.4831 - val_ac
curacy: 0.8529
Epoch 20/20
310/310 [=====] - 381s 1s/step - loss: 0.2490 - accuracy: 0.9073 - val_loss: 0.4113 - val_ac
curacy: 0.8801

```

## 7. Saving the Model as .h5 file and json file

```
In [28]: len(x_train)
```

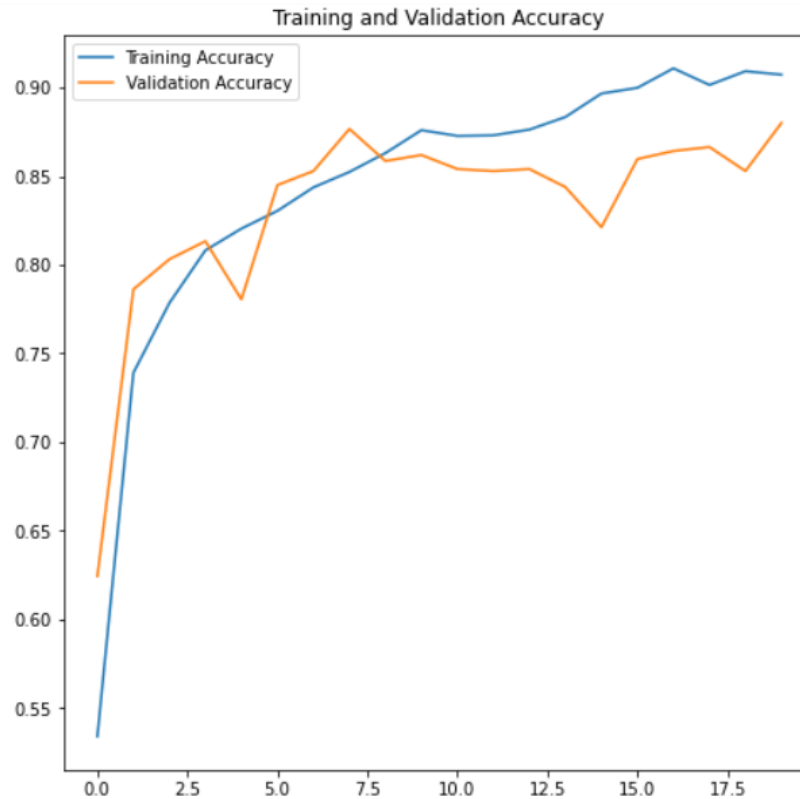
```
Out[28]: 310
```

```
In [29]: #saving the Model
model.save('Disaster_Classifier.h5')
model_json=model.to_json()
with open("model-bw.json","w") as json_file:
    json_file.write(model_json)
```

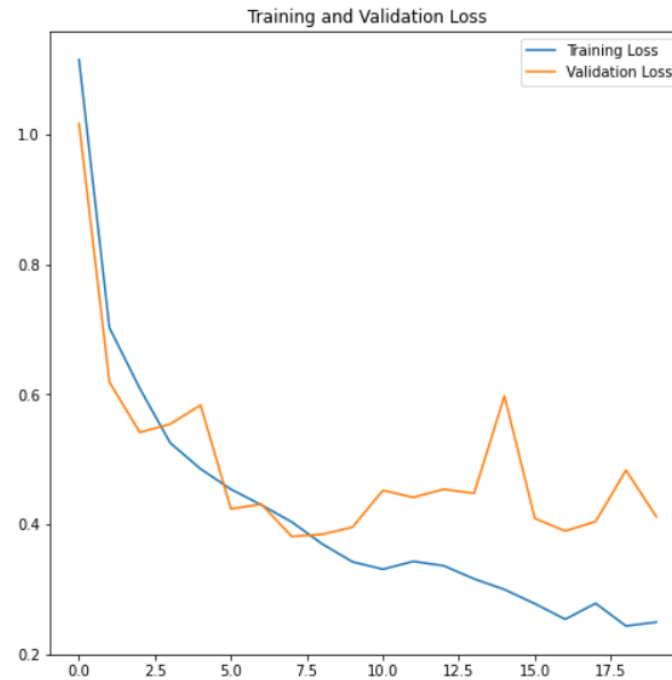
## 8. Plots for training vs validation accuracies and losses

```
In [30]: #Training and Validation Accuracy Plots
epochs_range = range(20)

plt.figure(figsize=(8, 8))
plt.plot(epochs_range, history.history['accuracy'], label='Training Accuracy')
plt.plot(epochs_range, history.history['val_accuracy'], label='Validation Accuracy')
plt.legend()
plt.title('Training and Validation Accuracy')
plt.show()
```



```
In [31]: #Training and Validation Loss Plot
plt.figure(figsize=(8, 8))
plt.plot(epochs_range, history.history['loss'], label='Training Loss')
plt.plot(epochs_range, history.history['val_loss'], label='Validation Loss')
plt.legend()
plt.title('Training and Validation Loss')
plt.show()
```



## 9. Testing the CNN Model with test data

```
In [35]: #Testing the CNN Model with test data
test_generator=test_datagen.flow_from_directory(r"/home/wsuser/work/dataset/test",
                                                target_size=(299,299),
                                                batch_size=447,
                                                color_mode='rgb',
                                                class_mode='categorical')
```

Found 447 images belonging to 4 classes.

```
In [36]: x_test, y_test = test_generator.__getitem__(0)
```

```
In [37]: y_test
```

```
Out[37]: array([[1., 0., 0., 0.],
               [0., 1., 0., 0.],
               [0., 0., 0., 1.],
               ...,
               [0., 0., 0., 1.],
               [0., 0., 0., 1.],
               [0., 0., 1., 0.]], dtype=float32)
```

```
In [38]: #predicting the labels of test data
y_pred = model.predict(x_test)
```

```
In [39]: y_pred = np.argmax(y_pred,axis=1)
```

```
In [40]: y_pred
```

```
Out[40]: array([0, 1, 3, 3, 1, 3, 2, 1, 1, 0, 0, 2, 3, 0, 2, 3, 3, 1, 1, 2, 2, 3,
                2, 0, 1, 3, 1, 3, 0, 1, 3, 0, 1, 3, 0, 1, 3, 2, 2, 1, 3, 1, 1, 0,
                2, 3, 2, 3, 2, 1, 3, 1, 2, 0, 1, 3, 0, 3, 3, 0, 0, 2, 0, 2, 0, 1,
                3, 1, 3, 0, 0, 0, 2, 1, 0, 1, 1, 0, 2, 2, 1, 0, 1, 0, 3, 3, 3, 2,
                2, 1, 1, 2, 2, 1, 1, 3, 1, 2, 3, 3, 1, 3, 0, 0, 1, 1, 1, 0, 0, 1,
                1, 2, 1, 0, 0, 1, 2, 2, 1, 2, 3, 1, 1, 2, 2, 1, 0, 1, 1, 1, 2, 1,
                3, 1, 0, 3, 2, 1, 2, 1, 3, 2, 2, 0, 1, 2, 0, 1, 1, 3, 0, 1, 0, 1,
                3, 1, 2, 1, 1, 1, 0, 1, 0, 3, 2, 0, 3, 0, 0, 0, 1, 0, 0, 2, 3, 2,
                0, 0, 1, 0, 0, 2, 2, 1, 0, 3, 1, 1, 1, 2, 0, 3, 1, 2, 3, 2, 0, 0,
                3, 1, 2, 1, 3, 3, 2, 0, 0, 2, 3, 1, 2, 2, 3, 1, 3, 1, 0, 0, 3, 1,
                3, 0, 1, 2, 2, 3, 1, 2, 2, 1, 1, 2, 1, 0, 1, 1, 2, 2, 2, 1, 0, 2,
                2, 3, 0, 1, 1, 3, 1, 0, 2, 2, 3, 0, 0, 3, 1, 0, 1, 1, 1, 1, 2, 0,
                3, 2, 0, 0, 3, 2, 3, 1, 1, 0, 1, 1, 2, 3, 1, 2, 0, 3, 3, 3, 1, 2,
                2, 2, 2, 2, 3, 3, 2, 1, 1, 1, 1, 3, 2, 3, 2, 1, 2, 2, 3, 2, 3, 2,
                2, 1, 3, 2, 2, 1, 1, 2, 0, 1, 2, 2, 3, 1, 2, 1, 2, 1, 2, 1, 3, 2,
                3, 2, 2, 3, 1, 3, 1, 3, 1, 0, 1, 2, 2, 2, 3, 0, 0, 2, 3, 3, 3, 1,
                2, 1, 3, 1, 1, 2, 0, 3, 2, 2, 0, 3, 1, 1, 1, 1, 1, 0, 1, 2, 0, 3,
                2, 0, 2, 2, 0, 1, 3, 3, 3, 2, 2, 2, 1, 1, 2, 0, 3, 1, 2, 1, 1, 1,
                2, 0, 3, 1, 2, 0, 2, 1, 3, 2, 3, 3, 1, 3, 2, 2, 1, 0, 3, 0, 0, 1,
                3, 3, 2, 2, 0, 1, 0, 2, 1, 2, 0, 1, 2, 1, 1, 3, 2, 3, 3, 1, 1, 1,
                3, 3, 0, 0, 3, 3, 2])
```

```
In [41]: y_test = np.argmax(y_test, axis=1)
```



```
In [42]: y_test
```

```
Out[42]: array([0, 1, 3, 3, 1, 3, 2, 1, 1, 0, 0, 2, 3, 0, 2, 3, 3, 2, 1, 3, 2, 3,
 0, 0, 1, 3, 1, 3, 0, 1, 3, 0, 1, 3, 0, 1, 3, 1, 2, 1, 3, 1, 1, 0,
 2, 3, 1, 3, 2, 1, 3, 0, 2, 0, 1, 3, 2, 3, 3, 0, 0, 2, 0, 2, 0, 1,
 3, 1, 3, 0, 0, 0, 2, 1, 0, 1, 1, 0, 2, 2, 1, 0, 1, 0, 3, 3, 3, 2,
 2, 1, 1, 2, 2, 2, 1, 3, 1, 2, 3, 3, 1, 3, 0, 0, 1, 1, 1, 0, 0, 3,
 1, 2, 1, 0, 0, 1, 2, 2, 1, 2, 3, 1, 1, 2, 2, 2, 0, 1, 2, 1, 1, 0,
 3, 1, 0, 3, 2, 1, 2, 1, 3, 2, 2, 3, 1, 2, 0, 1, 3, 2, 3, 1, 0, 1,
 3, 3, 3, 1, 1, 1, 0, 1, 0, 3, 2, 0, 3, 0, 0, 0, 2, 0, 0, 2, 3, 2,
 0, 0, 1, 0, 0, 2, 2, 1, 0, 3, 1, 1, 1, 2, 0, 3, 1, 3, 3, 2, 0, 0,
 3, 1, 2, 1, 3, 3, 2, 0, 1, 1, 3, 1, 2, 0, 1, 1, 3, 3, 0, 0, 3, 0,
 3, 0, 2, 2, 2, 3, 1, 2, 2, 1, 1, 2, 1, 0, 1, 1, 2, 2, 2, 1, 0, 2,
 2, 3, 0, 2, 1, 3, 1, 0, 2, 1, 3, 0, 0, 3, 0, 0, 1, 0, 1, 1, 2, 0,
 3, 2, 1, 0, 3, 2, 3, 1, 1, 0, 1, 1, 1, 3, 1, 2, 0, 3, 3, 3, 1, 2,
 3, 2, 2, 1, 3, 3, 3, 1, 1, 1, 1, 3, 2, 3, 1, 1, 2, 3, 3, 2, 3, 2,
 2, 1, 3, 2, 2, 1, 1, 1, 0, 1, 2, 2, 3, 1, 2, 1, 2, 1, 2, 1, 3, 1,
 3, 2, 2, 3, 1, 3, 1, 3, 1, 0, 1, 2, 2, 2, 3, 0, 0, 2, 3, 0, 3, 1,
 2, 2, 3, 1, 1, 2, 0, 3, 2, 2, 0, 3, 1, 0, 0, 1, 1, 0, 1, 2, 0, 3,
 2, 0, 2, 2, 0, 1, 3, 3, 3, 1, 2, 2, 1, 1, 2, 0, 3, 1, 2, 1, 1, 1,
 2, 0, 3, 2, 2, 0, 0, 1, 3, 2, 3, 3, 1, 3, 2, 2, 1, 0, 3, 0, 0, 1,
 3, 3, 2, 2, 0, 1, 0, 2, 1, 1, 0, 1, 2, 1, 1, 3, 1, 3, 3, 1, 1, 1,
 3, 3, 0, 0, 3, 3, 2])
```

## 10. Generating Classification Report with F1 Score

```
In [44]: import keras.backend as K
def accuracy(y_true, y_pred):
    '''Calculates the mean accuracy rate across all predictions for binary
    classification problems.
    '''
    return K.mean(K.equal(y_true, K.round(y_pred)))
```

```
In [45]: #Classification report with Accuracy (F1 Score) for each Class
print("CNN Disaster Classification Model Accuracy on test set: {:.4f}".format(accuracy(y_test, y_pred)))
print(classification_report(y_test, y_pred))
```

CNN Disaster Classification Model Accuracy on test set: 0.8881

	precision	recall	f1-score	support
0	0.94	0.88	0.91	94
1	0.86	0.88	0.87	136
2	0.82	0.90	0.85	108
3	0.97	0.89	0.93	109
accuracy			0.89	447
macro avg	0.90	0.89	0.89	447
weighted avg	0.89	0.89	0.89	447

## 11. Weighted Accuracy of the model

```
In [50]: #Weighted Accuracy of the model
accu = np.count_nonzero(np.equal(y_pred,y_test))/x_test.shape[0]
print("Accuracy: {} %".format(accu*100))
```

Accuracy: 88.81431767337807 %

## 12. Confusion Matrix for test data

```
In [50]: #Weighted Accuracy of the model
accu = np.count_nonzero(np.equal(y_pred,y_test))/x_test.shape[0]
print("Accuracy: {} %".format(accu*100))
```

Accuracy: 88.81431767337807 %

```
In [51]: classes = list(x_train.class_indices.keys())
```

```
In [53]: #Confusion matrix for test data Classification
import pandas as pd
df_cmatrix = pd.DataFrame(confusion_matrix(y_test, y_pred),index=classes, columns=classes)
sns.set(font_scale=1.0)
fig,ax = plt.subplots(figsize=(16,12))
sns.heatmap(df_cmatrix, annot=True,annot_kws={"size": 15},fmt='2g')
```

