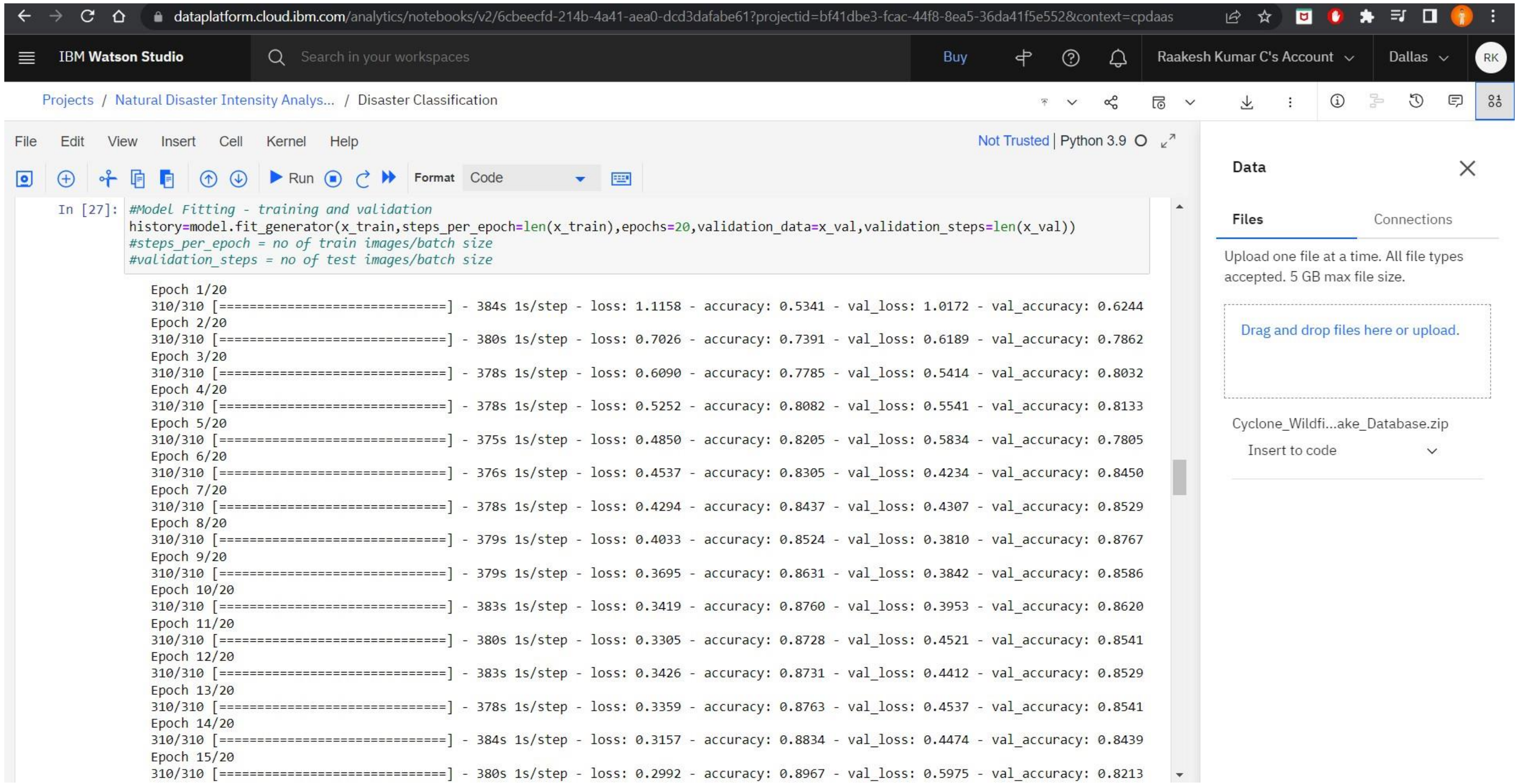
Project Development Phase
Sprint - II

Date	27 November 2022
Team ID	PNT2022TMID45772
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

Link:
https://dataplatform.cloud.ibm.com/analytics/notebooks/v2/6cbeecfd-214b-4a41-aea0-dcd3dafabe61/view?access_token=cc793da694f128bd71a83af2dd03af6db746baa06c11850fce55b299b697b05a




```
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
```

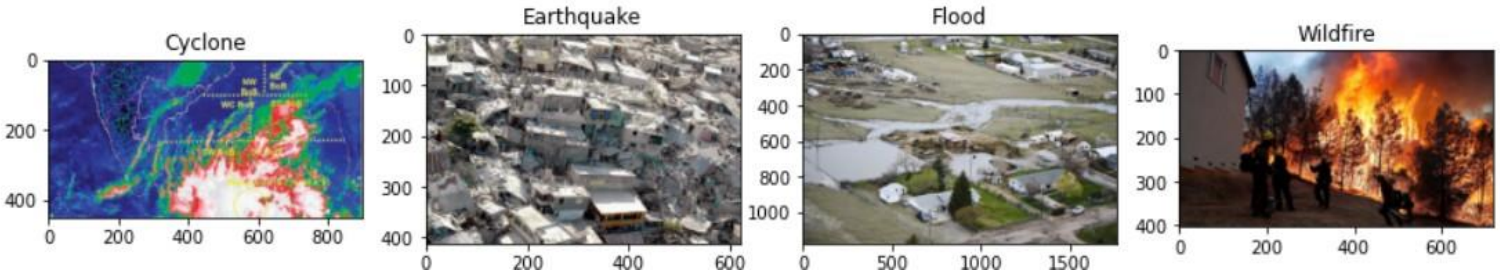
1. Indexing Disaster Classes

```
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/wor
         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 (MaxPooling  (None, 73, 73, 64)       0
 2D)

 dropout (Dropout)           (None, 73, 73, 64)        0

 conv2d_2 (Conv2D)           (None, 71, 71, 32)        18464

 max_pooling2d_2 (MaxPooling  (None, 35, 35, 32)       0
 2D)

 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
```

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_
#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_ac
curacy: 0.6244
Epoch 2/20
310/310 [==============================] - 380s 1s/step - loss: 0.7026 - accuracy: 0.7391 - val_loss: 0.6189 - val_ac
curacy: 0.7862
Epoch 3/20
310/310 [==============================] - 378s 1s/step - loss: 0.6090 - accuracy: 0.7785 - val_loss: 0.5414 - val_ac
curacy: 0.8032
Epoch 4/20
310/310 [==============================] - 378s 1s/step - loss: 0.5252 - accuracy: 0.8082 - val_loss: 0.5541 - val_ac
curacy: 0.8133
Epoch 5/20
310/310 [==============================] - 375s 1s/step - loss: 0.4850 - accuracy: 0.8205 - val_loss: 0.5834 - val_ac
curacy: 0.7805
Epoch 6/20
310/310 [==============================] - 376s 1s/step - loss: 0.4537 - accuracy: 0.8305 - val_loss: 0.4234 - val_ac
curacy: 0.8450
Epoch 7/20
310/310 [==============================] - 378s 1s/step - loss: 0.4294 - accuracy: 0.8437 - val_loss: 0.4307 - val_ac
curacy: 0.8529
Epoch 8/20
310/310 [==============================] - 379s 1s/step - loss: 0.4033 - accuracy: 0.8524 - val_loss: 0.3810 - val_ac
curacy: 0.8767
Epoch 9/20
310/310 [==============================] - 379s 1s/step - loss: 0.3695 - accuracy: 0.8631 - val_loss: 0.3842 - val_ac
curacy: 0.8586
Epoch 10/20
310/310 [==============================] - 383s 1s/step - loss: 0.3419 - accuracy: 0.8760 - val_loss: 0.3953 - val_ac
```

```
Epoch 11/20
310/310 [==============================] - 380s 1s/step - loss: 0.3305 - accuracy: 0.8728 - val_loss: 0.4521 - val_ac
curacy: 0.8541
Epoch 12/20
310/310 [==============================] - 383s 1s/step - loss: 0.3426 - accuracy: 0.8731 - val_loss: 0.4412 - val_ac
curacy: 0.8529
Epoch 13/20
310/310 [==============================] - 378s 1s/step - loss: 0.3359 - accuracy: 0.8763 - val_loss: 0.4537 - val_ac
curacy: 0.8541
Epoch 14/20
310/310 [==============================] - 384s 1s/step - loss: 0.3157 - accuracy: 0.8834 - val_loss: 0.4474 - val_ac
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)
```

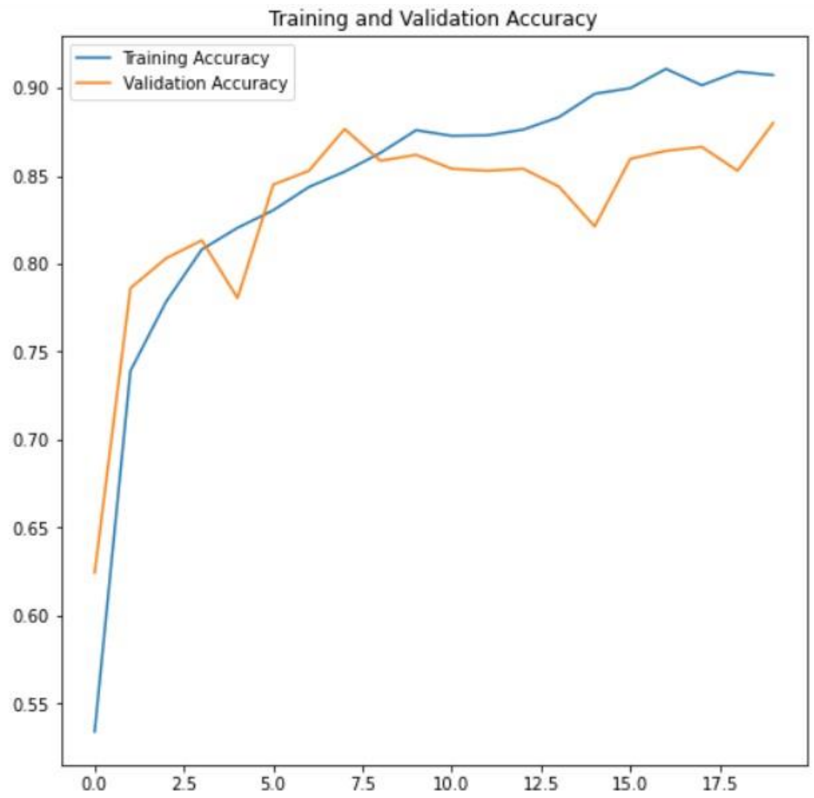
Out[28]:
```
310
```

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)
```

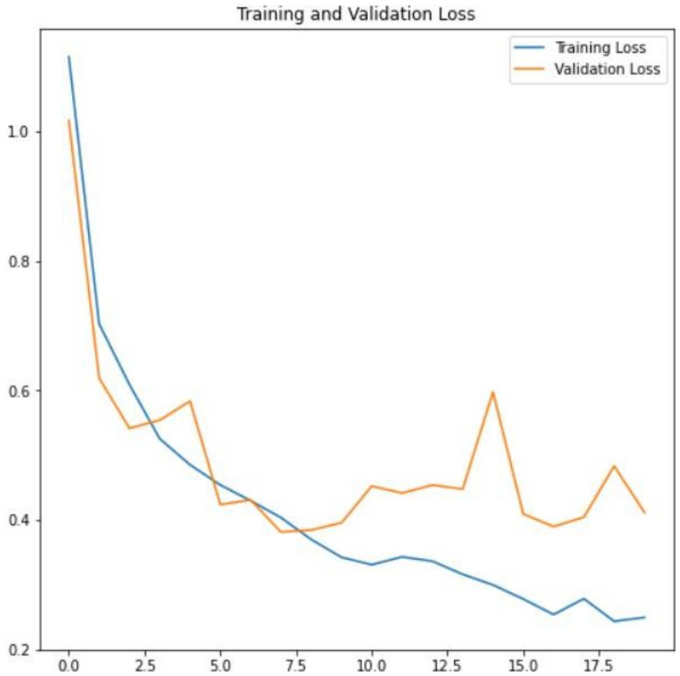
8. Plots for training vs validation accuracies and losses

```
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]:
```python
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]:
```python
#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')
```