1. Importing Libraries & Load the file

In [1]:

```
import numpy as np
import pandas as pd
import tensorflow as tf
from tensorflow import keras
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from keras.layers import Conv2D, MaxPool2D, AveragePooling2D, Input, BatchNormalization,
MaxPooling2D, Activation, Flatten, Dense, Dropout
from keras.models import Sequential
from keras.utils import np_utils
from sklearn.metrics import classification_report
from imblearn.over_sampling import RandomOverSampler
from keras.preprocessing import image
import scipy
import os
import cv2
```

In [2]:

```
# Reading Dataset
data = pd.read_csv('/content/drive/MyDrive/Thesis Work - Facial Expression Detection & Re
cognition using Deep Learning/Dataset/fer2013.csv')
data.head(10)
```

Out[2]:

	emotion	pixels	Usage
0	0	70 80 82 72 58 58 60 63 54 58 60 48 89 115 121...	Training
1	0	151 150 147 155 148 133 111 140 170 174 182 15...	Training
2	2	231 212 156 164 174 138 161 173 182 200 106 38...	Training
3	4	24 32 36 30 32 23 19 20 30 41 21 22 32 34 21 1...	Training
4	6	4 0 0 0 0 0 0 0 0 0 0 0 0 3 15 23 28 48 50 58 84...	Training
5	2	55 55 55 55 55 54 60 68 54 85 151 163 170 179 ...	Training
6	4	20 17 19 21 25 38 42 42 46 54 56 62 63 66 82 1...	Training
7	3	77 78 79 79 78 75 60 55 47 48 58 73 77 79 57 5...	Training
8	3	85 84 90 121 101 102 133 153 153 169 177 189 1...	Training
9	2	255 254 255 254 254 179 122 107 95 124 149 150...	Training

In [3]:

```
# Checking Shape of data
data.shape
```

Out[3]:

```
(35887, 3)
```

2. Data Visualization

In [4]:

```
label_to_text = {0:'anger', 1:'disgust', 2:'fear', 3:'happiness', 4: 'sadness', 5: 'surp
rise', 6: 'neutral'}
```

```
label_to_text
```

Out[4]:

```
{0: 'anger',
 1: 'disgust',
 2: 'fear',
 3: 'happiness',
 4: 'sadness',
 5: 'surprise',
 6: 'neutral'}
```

In [5]:

```
fig = plt.figure(1, (14, 14))
k = 0
for label in sorted(data.emotion.unique()):
    for j in range(5):
        px = data[data.emotion==label].pixels.iloc[k]
        px = np.array(px.split(' ')).reshape(48, 48).astype('float32')
        k += 1
        ax = plt.subplot(7, 7, k)
        ax.imshow(px)
        ax.set_xticks([])
        ax.set_yticks([])
        ax.set_title(label_to_text[label])
        plt.tight_layout()
```

In [6]:

```
# Checking Emotion Class Distribution
data['emotion'].value_counts()
```

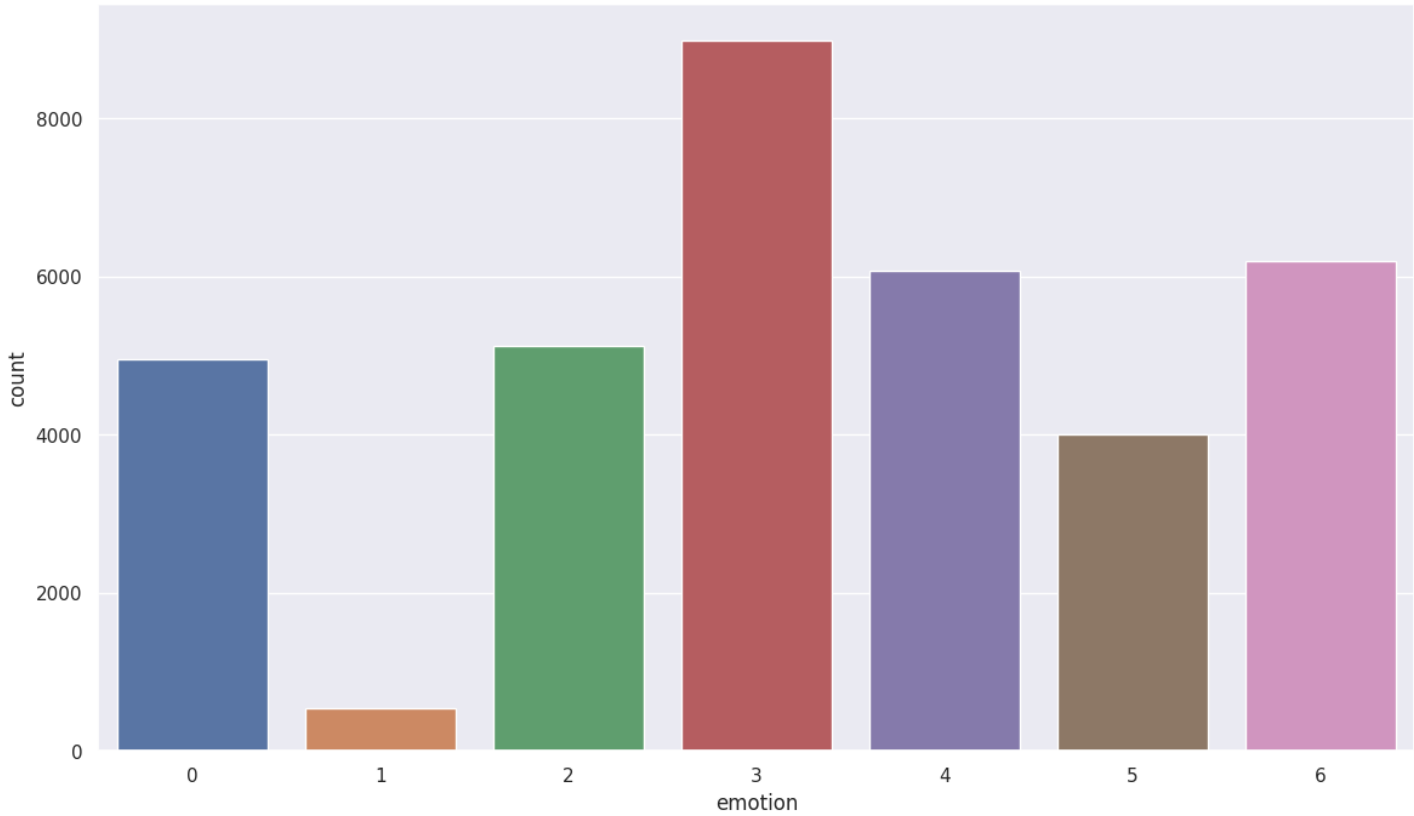
Out[6]:

```
3    8989
6    6198
4    6077
```

```
2    5121
0    4953
5    4002
1     547
Name: emotion, dtype: int64
```

In [7]:

```
# Plotting the above distribution
plt.figure(figsize=(14, 8))
sns.set_theme(style="darkgrid")
ax = sns.countplot(x="emotion", data=data)
```



From the above chart, we can observe that the data is highly imbalnace and for some emotions we have very small number of images, so we need to balnce the data by oversampling technique, so to that enough number of images for every emotions(class).

3. Data Pre-processing (Balancing & Preparation)

In [8]:

```
# Split the data into feature & target variable
x_data = data['pixels']
y_data = data['emotion']
```

In [9]:

```
# Perform Random Over Sampling to balance the data
oversampler = RandomOverSampler(sampling_strategy='auto')

x_data, y_data = oversampler.fit_resample(x_data.values.reshape(-1,1), y_data)
print(x_data.shape," ",y_data.shape)
```

```
(62923, 1)   (62923,)
```

In [10]:

```
# Let's check the distributio of target data again after balancing
y_data.value_counts()
```

Out[10]:

```
0    8989
2    8989
4    8989
6    8989
3    8989
5    8989
1    8989
Name: emotion, dtype: int64
```

In [11]:

```
x_data = pd.Series(x_data.flatten())
x_data
```

Out[11]:

```
0        70 80 82 72 58 58 60 63 54 58 60 48 89 115 121...
1        151 150 147 155 148 133 111 140 170 174 182 15...
2        231 212 156 164 174 138 161 173 182 200 106 38...
3        24 32 36 30 32 23 19 20 30 41 21 22 32 34 21 1...
4        4 0 0 0 0 0 0 0 0 0 0 0 3 15 23 28 48 50 58 84...
                                ...
62918    171 172 158 147 123 86 87 99 102 102 102 103 1...
62919    66 72 78 80 80 84 86 86 90 55 2 2 25 53 81 86 ...
62920    41 45 29 37 49 38 34 38 26 18 21 36 22 14 16 1...
62921    0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ...
62922    90 93 117 104 103 76 84 71 49 68 80 78 106 208...
Length: 62923, dtype: object
```

In [12]:

```
# Normalize the data
x_data = np.array(list(map(str.split, x_data)), np.float32)
x_data/=255
x_data[:10]
```

Out[12]:

```
array([[0.27450982, 0.3137255 , 0.32156864, ..., 0.41568628, 0.42745098,
        0.32156864],
       [0.5921569 , 0.5882353 , 0.5764706 , ..., 0.75686276, 0.7176471 ,
        0.72156864],
       [0.90588236, 0.83137256, 0.6117647 , ..., 0.34509805, 0.43137255,
        0.59607846],
       ...,
       [0.3019608 , 0.30588236, 0.30980393, ..., 0.49019608, 0.2627451 ,
        0.26666668],
       [0.33333334, 0.32941177, 0.3529412 , ..., 0.22745098, 0.28627452,
        0.32941177],
       [1.        , 0.99607843, 1.        , ..., 0.99607843, 1.        ,
        1.        ]], dtype=float32)
```

In [13]:

```
# Reshaping
x_data = x_data.reshape(-1, 48, 48, 1)
x_data.shape
```

Out[13]:

```
(62923, 48, 48, 1)
```

In [14]:

```
y_data = np.array(y_data)
y_data = y_data.reshape(y_data.shape[0], 1)
y_data.shape
```

Out[14]:

```
(62923, 1)
```

In [15]:

```
# Split the data and create train-test set
x_train, x_test, y_train, y_test = train_test_split(x_data, y_data, test_size = 0.1, ran
dom_state = 45)
```

In [16]:

```
x_train.shape, x_test.shape, y_train.shape, y_test.shape
```

Out[16]:

```
((56630, 48, 48, 1), (6293, 48, 48, 1), (56630, 1), (6293, 1))
```

In [17]:

```
# Perform One-Hot Encoding on training data
y_train = np_utils.to_categorical(y_train, 7)
y_train.shape
```

Out[17]:

```
(56630, 7)
```

In [18]:

```
# Perform One-Hot Encoding on test data
y_test = np_utils.to_categorical(y_test, 7)
y_test.shape
```

Out[18]:

```
(6293, 7)
```

4. Model Building

In [19]:

```
model = Sequential([
    # 1st Conv Layer
    Input((48, 48, 1)),
    Conv2D(32, kernel_size=(3,3), strides=(1,1), padding='valid'),
    BatchNormalization(axis=3),
    Activation('relu'),
    Dropout(0.25),

    # 2nd Conv Layer
    Conv2D(64, (3,3), strides=(1,1), padding = 'same'),
    BatchNormalization(axis=3),
    Activation('relu'),
    MaxPooling2D((2,2)),

    # 3rd Conv Layer
    Conv2D(64, (3,3), strides=(1,1), padding = 'valid'),
    BatchNormalization(axis=3),
    Activation('relu'),
    Dropout(0.25),

    # 4th Conv Layer
    Conv2D(128, (3,3), strides=(1,1), padding = 'same'),
    BatchNormalization(axis=3),
    Activation('relu'),
    MaxPooling2D((2,2)),

    # 5th Conv Layer
    Conv2D(128, (3,3), strides=(1,1), padding = 'valid'),
    BatchNormalization(axis=3),
    Activation('relu'),
    MaxPooling2D((2,2)),

    # Flattening the Layer
    Flatten(),
```

```python
    # Hidden Layer
    Dense(250, activation='relu'),
    Dropout(0.5),

    # Output Layer
    Dense(7, activation = 'softmax')
])
```

In [20]:

```python
model.summary()
```

```
Model: "sequential"

_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d (Conv2D)             (None, 46, 46, 32)        320       
                                                                 
 batch_normalization (BatchN  (None, 46, 46, 32)       128       
 ormalization)                                                   
                                                                 
 activation (Activation)     (None, 46, 46, 32)        0         
                                                                 
 dropout (Dropout)           (None, 46, 46, 32)        0         
                                                                 
 conv2d_1 (Conv2D)           (None, 46, 46, 64)        18496     
                                                                 
 batch_normalization_1 (Batc  (None, 46, 46, 64)       256       
 hNormalization)                                                 
                                                                 
 activation_1 (Activation)   (None, 46, 46, 64)        0         
                                                                 
 max_pooling2d (MaxPooling2D  (None, 23, 23, 64)       0         
 )                                                               
                                                                 
 conv2d_2 (Conv2D)           (None, 21, 21, 64)        36928     
                                                                 
 batch_normalization_2 (Batc  (None, 21, 21, 64)       256       
 hNormalization)                                                 
                                                                 
 activation_2 (Activation)   (None, 21, 21, 64)        0         
                                                                 
 dropout_1 (Dropout)         (None, 21, 21, 64)        0         
                                                                 
 conv2d_3 (Conv2D)           (None, 21, 21, 128)       73856     
                                                                 
 batch_normalization_3 (Batc  (None, 21, 21, 128)      512       
 hNormalization)                                                 
                                                                 
 activation_3 (Activation)   (None, 21, 21, 128)       0         
                                                                 
 max_pooling2d_1 (MaxPooling  (None, 10, 10, 128)      0         
 2D)                                                             
                                                                 
 conv2d_4 (Conv2D)           (None, 8, 8, 128)         147584    
                                                                 
 batch_normalization_4 (Batc  (None, 8, 8, 128)        512       
 hNormalization)                                                 
                                                                 
 activation_4 (Activation)   (None, 8, 8, 128)         0         
                                                                 
 max_pooling2d_2 (MaxPooling  (None, 4, 4, 128)        0         
 2D)                                                             
                                                                 
 flatten (Flatten)           (None, 2048)              0         
                                                                 
 dense (Dense)               (None, 250)               512250    
                                                                 
 dropout_2 (Dropout)         (None, 250)               0         
                                                                 
 dense_1 (Dense)             (None, 7)                 1757      
```

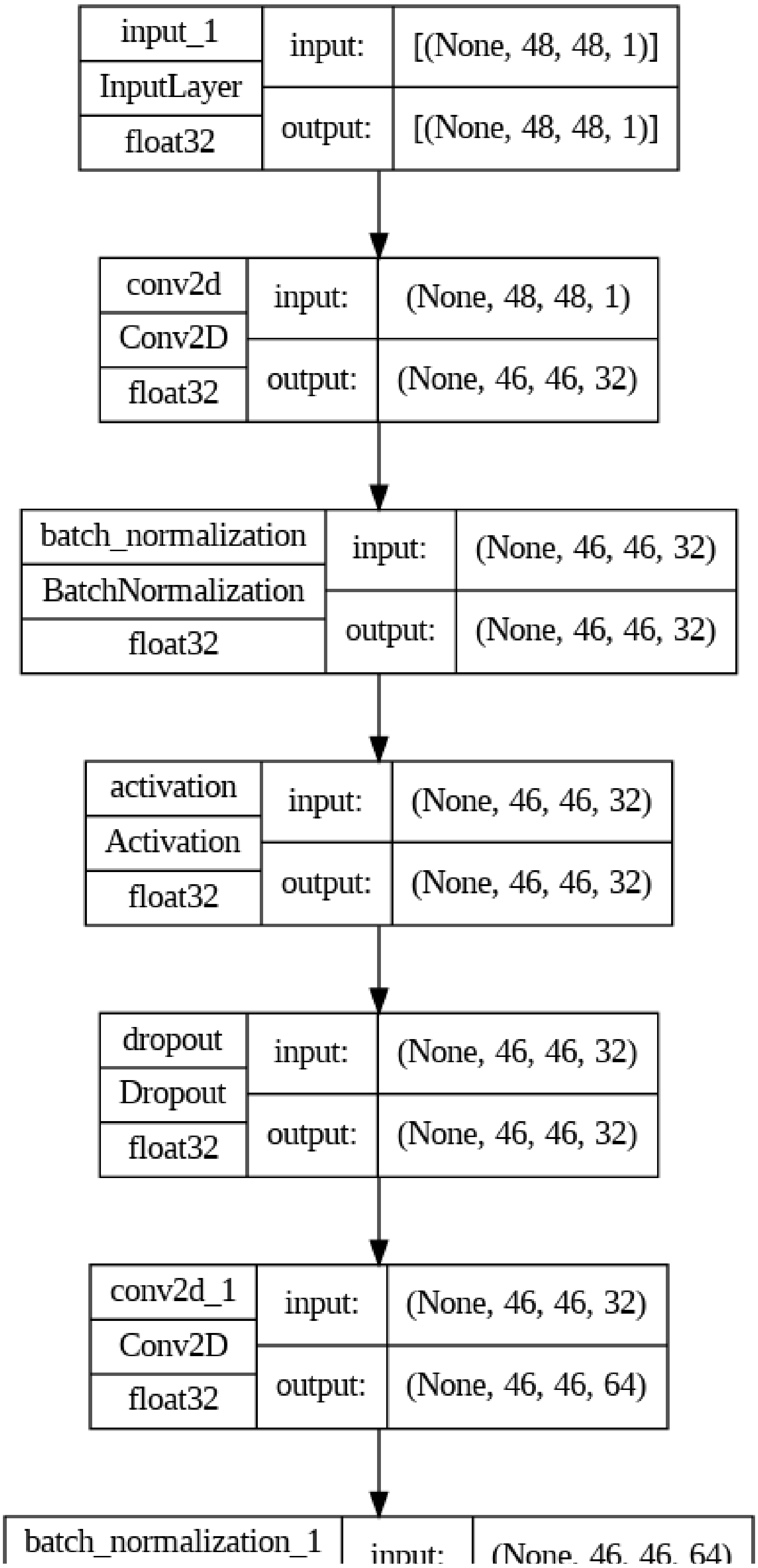
```
=================================================================
Total params: 792,855
Trainable params: 792,023
Non-trainable params: 832
_________________________________________________________________
```

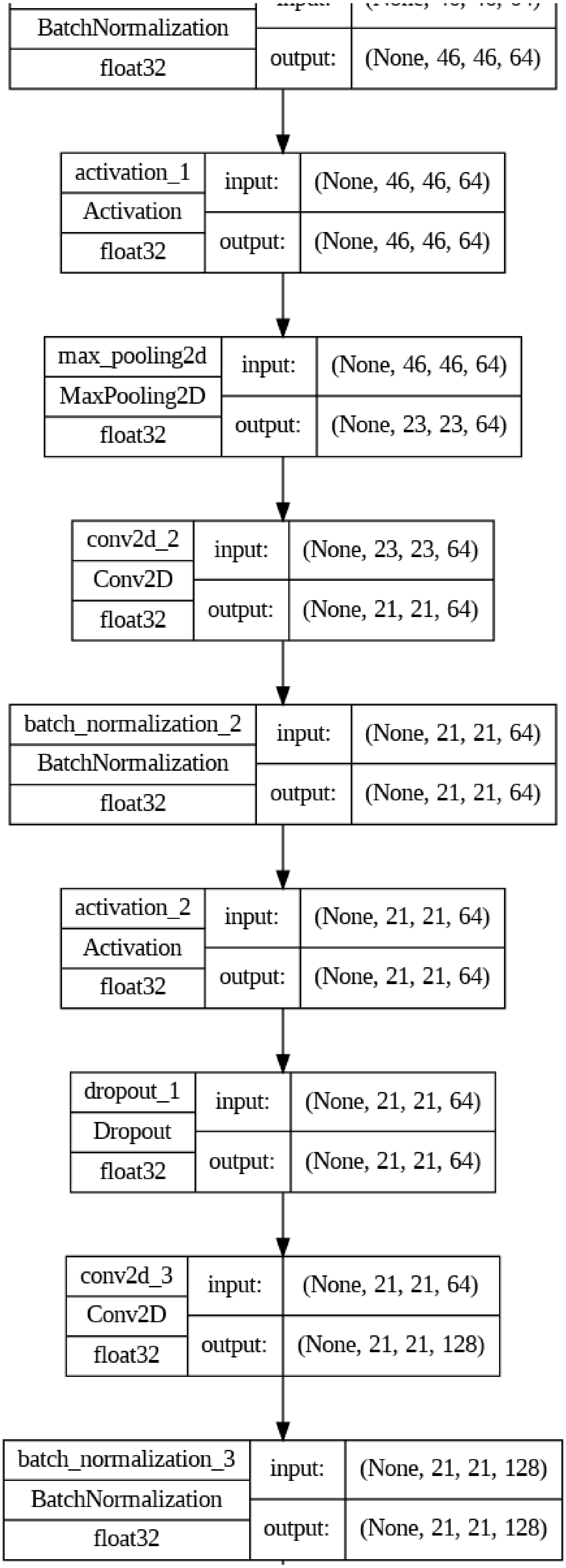
5. Model Training

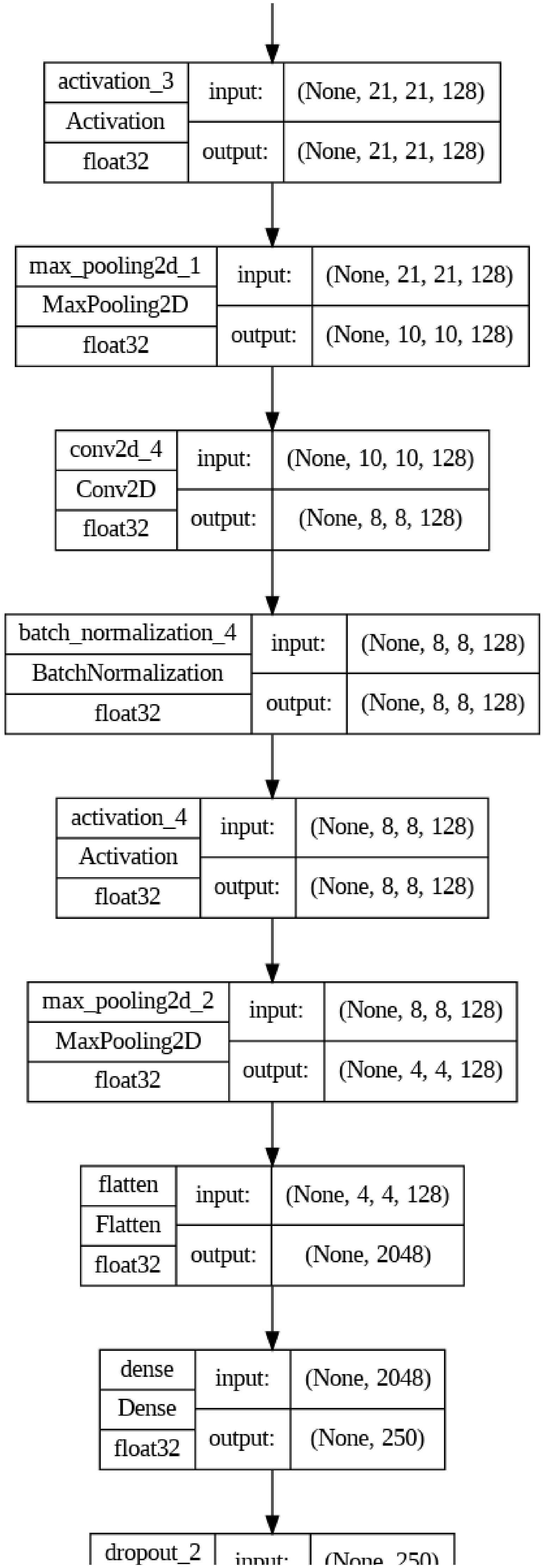
In [21]:

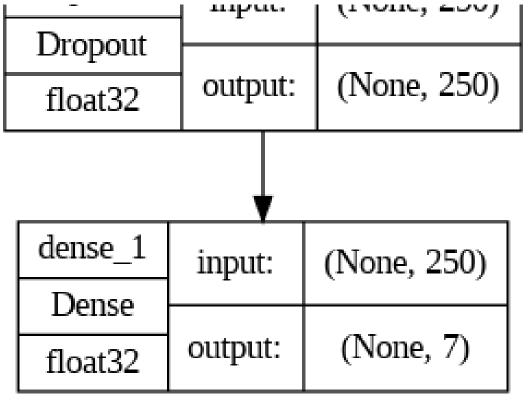
```python
# Model Flowchart
tf.keras.utils.plot_model(model, to_file = "/content/drive/MyDrive/Thesis Work - Facial Expression Detection & Recognition using Deep Learning/best_model.png", show_shapes = True, show_dtype = True)
```

Out[21]:




BatchNormalization
float32
output:
(None, 46, 46, 64)
activation_1
Activation
float32
input:
(None, 46, 46, 64)
output:
(None, 46, 46, 64)
max_pooling2d
MaxPooling2D
float32
input:
(None, 46, 46, 64)
output:
(None, 23, 23, 64)
conv2d_2
Conv2D
float32
input:
(None, 23, 23, 64)
output:
(None, 21, 21, 64)
batch_normalization_2
BatchNormalization
float32
input:
(None, 21, 21, 64)
output:
(None, 21, 21, 64)
activation_2
Activation
float32
input:
(None, 21, 21, 64)
output:
(None, 21, 21, 64)
dropout_1
Dropout
float32
input:
(None, 21, 21, 64)
output:
(None, 21, 21, 64)
conv2d_3
Conv2D
float32
input:
(None, 21, 21, 64)
output:
(None, 21, 21, 128)
batch_normalization_3
BatchNormalization
float32
input:
(None, 21, 21, 128)
output:
(None, 21, 21, 128)


activation_3
Activation
float32
input:
(None, 21, 21, 128)
output:
(None, 21, 21, 128)
max_pooling2d_1
MaxPooling2D
float32
input:
(None, 21, 21, 128)
output:
(None, 10, 10, 128)
conv2d_4
Conv2D
float32
input:
(None, 10, 10, 128)
output:
(None, 8, 8, 128)
batch_normalization_4
BatchNormalization
float32
input:
(None, 8, 8, 128)
output:
(None, 8, 8, 128)
activation_4
Activation
float32
input:
(None, 8, 8, 128)
output:
(None, 8, 8, 128)
max_pooling2d_2
MaxPooling2D
float32
input:
(None, 8, 8, 128)
output:
(None, 4, 4, 128)
flatten
Flatten
float32
input:
(None, 4, 4, 128)
output:
(None, 2048)
dense
Dense
float32
input:
(None, 2048)
output:
(None, 250)
dropout_2



In [22]:

```
# Compile the Model
adam = keras.optimizers.Adam(learning_rate=0.0001)
model.compile(optimizer=adam, loss='categorical_crossentropy', metrics=['accuracy'])
```

In [23]:

```
# Train the Model
history = model.fit(x_train, y_train, epochs = 35, validation_data=(x_test, y_test))
```

```
Epoch 1/35
1770/1770 [==============================] - 45s 17ms/step - loss: 1.8193 - accuracy: 0.2
754 - val_loss: 1.7512 - val_accuracy: 0.3261
Epoch 2/35
1770/1770 [==============================] - 31s 17ms/step - loss: 1.5353 - accuracy: 0.4
115 - val_loss: 1.4483 - val_accuracy: 0.4602
Epoch 3/35
1770/1770 [==============================] - 31s 17ms/step - loss: 1.3744 - accuracy: 0.4
779 - val_loss: 1.2652 - val_accuracy: 0.5152
Epoch 4/35
1770/1770 [==============================] - 31s 17ms/step - loss: 1.2593 - accuracy: 0.5
227 - val_loss: 1.1853 - val_accuracy: 0.5443
Epoch 5/35
1770/1770 [==============================] - 31s 18ms/step - loss: 1.1733 - accuracy: 0.5
566 - val_loss: 1.1039 - val_accuracy: 0.5710
Epoch 6/35
1770/1770 [==============================] - 31s 17ms/step - loss: 1.1032 - accuracy: 0.5
830 - val_loss: 1.0158 - val_accuracy: 0.6105
Epoch 7/35
1770/1770 [==============================] - 31s 17ms/step - loss: 1.0455 - accuracy: 0.6
052 - val_loss: 1.0199 - val_accuracy: 0.6027
Epoch 8/35
1770/1770 [==============================] - 31s 17ms/step - loss: 1.0003 - accuracy: 0.6
196 - val_loss: 0.9581 - val_accuracy: 0.6301
Epoch 9/35
1770/1770 [==============================] - 30s 17ms/step - loss: 0.9593 - accuracy: 0.6
351 - val_loss: 0.9383 - val_accuracy: 0.6426
Epoch 10/35
1770/1770 [==============================] - 30s 17ms/step - loss: 0.9210 - accuracy: 0.6
503 - val_loss: 0.9138 - val_accuracy: 0.6585
Epoch 11/35
1770/1770 [==============================] - 30s 17ms/step - loss: 0.8878 - accuracy: 0.6
632 - val_loss: 0.8732 - val_accuracy: 0.6606
Epoch 12/35
1770/1770 [==============================] - 30s 17ms/step - loss: 0.8581 - accuracy: 0.6
774 - val_loss: 0.8311 - val_accuracy: 0.6860
Epoch 13/35
1770/1770 [==============================] - 30s 17ms/step - loss: 0.8272 - accuracy: 0.6
868 - val_loss: 0.8103 - val_accuracy: 0.6906
Epoch 14/35
1770/1770 [==============================] - 31s 17ms/step - loss: 0.8015 - accuracy: 0.6
975 - val_loss: 0.8235 - val_accuracy: 0.6943
Epoch 15/35
1770/1770 [==============================] - 32s 18ms/step - loss: 0.7718 - accuracy: 0.7
090 - val_loss: 0.8012 - val_accuracy: 0.7071
Epoch 16/35
1770/1770 [==============================] - 30s 17ms/step - loss: 0.7458 - accuracy: 0.7
```

```
203 - val_loss: 0.7640 - val_accuracy: 0.7116
Epoch 17/35
1770/1770 [==============================] - 31s 17ms/step - loss: 0.7203 - accuracy: 0.7
305 - val_loss: 0.7170 - val_accuracy: 0.7388
Epoch 18/35
1770/1770 [==============================] - 31s 17ms/step - loss: 0.6940 - accuracy: 0.7
420 - val_loss: 0.7004 - val_accuracy: 0.7421
Epoch 19/35
1770/1770 [==============================] - 31s 17ms/step - loss: 0.6670 - accuracy: 0.7
513 - val_loss: 0.6960 - val_accuracy: 0.7500
Epoch 20/35
1770/1770 [==============================] - 31s 17ms/step - loss: 0.6498 - accuracy: 0.7
558 - val_loss: 0.6844 - val_accuracy: 0.7512
Epoch 21/35
1770/1770 [==============================] - 30s 17ms/step - loss: 0.6293 - accuracy: 0.7
669 - val_loss: 0.7102 - val_accuracy: 0.7435
Epoch 22/35
1770/1770 [==============================] - 31s 18ms/step - loss: 0.6121 - accuracy: 0.7
734 - val_loss: 0.7051 - val_accuracy: 0.7534
Epoch 23/35
1770/1770 [==============================] - 31s 17ms/step - loss: 0.5873 - accuracy: 0.7
826 - val_loss: 0.6534 - val_accuracy: 0.7685
Epoch 24/35
1770/1770 [==============================] - 32s 18ms/step - loss: 0.5685 - accuracy: 0.7
902 - val_loss: 0.6455 - val_accuracy: 0.7763
Epoch 25/35
1770/1770 [==============================] - 32s 18ms/step - loss: 0.5507 - accuracy: 0.7
968 - val_loss: 0.6369 - val_accuracy: 0.7772
Epoch 26/35
1770/1770 [==============================] - 31s 18ms/step - loss: 0.5329 - accuracy: 0.8
046 - val_loss: 0.6132 - val_accuracy: 0.7971
Epoch 27/35
1770/1770 [==============================] - 32s 18ms/step - loss: 0.5171 - accuracy: 0.8
109 - val_loss: 0.6108 - val_accuracy: 0.7950
Epoch 28/35
1770/1770 [==============================] - 31s 17ms/step - loss: 0.4972 - accuracy: 0.8
170 - val_loss: 0.6366 - val_accuracy: 0.7894
Epoch 29/35
1770/1770 [==============================] - 32s 18ms/step - loss: 0.4821 - accuracy: 0.8
218 - val_loss: 0.6100 - val_accuracy: 0.8031
Epoch 30/35
1770/1770 [==============================] - 30s 17ms/step - loss: 0.4693 - accuracy: 0.8
287 - val_loss: 0.6049 - val_accuracy: 0.8007
Epoch 31/35
1770/1770 [==============================] - 30s 17ms/step - loss: 0.4529 - accuracy: 0.8
337 - val_loss: 0.6012 - val_accuracy: 0.8069
Epoch 32/35
1770/1770 [==============================] - 31s 18ms/step - loss: 0.4370 - accuracy: 0.8
401 - val_loss: 0.5891 - val_accuracy: 0.8154
Epoch 33/35
1770/1770 [==============================] - 30s 17ms/step - loss: 0.4227 - accuracy: 0.8
453 - val_loss: 0.6112 - val_accuracy: 0.8072
Epoch 34/35
1770/1770 [==============================] - 30s 17ms/step - loss: 0.4101 - accuracy: 0.8
505 - val_loss: 0.6054 - val_accuracy: 0.8147
Epoch 35/35
1770/1770 [==============================] - 31s 18ms/step - loss: 0.4007 - accuracy: 0.8
528 - val_loss: 0.6056 - val_accuracy: 0.8131
```

6. Model Evaluation

In [25]:

```
print("Accuracy of our model on test data : " , model.evaluate(x_test, y_test)[1]*100 ,
"%")
print("Loss of our model on test data : " , model.evaluate(x_test, y_test)[0])
```

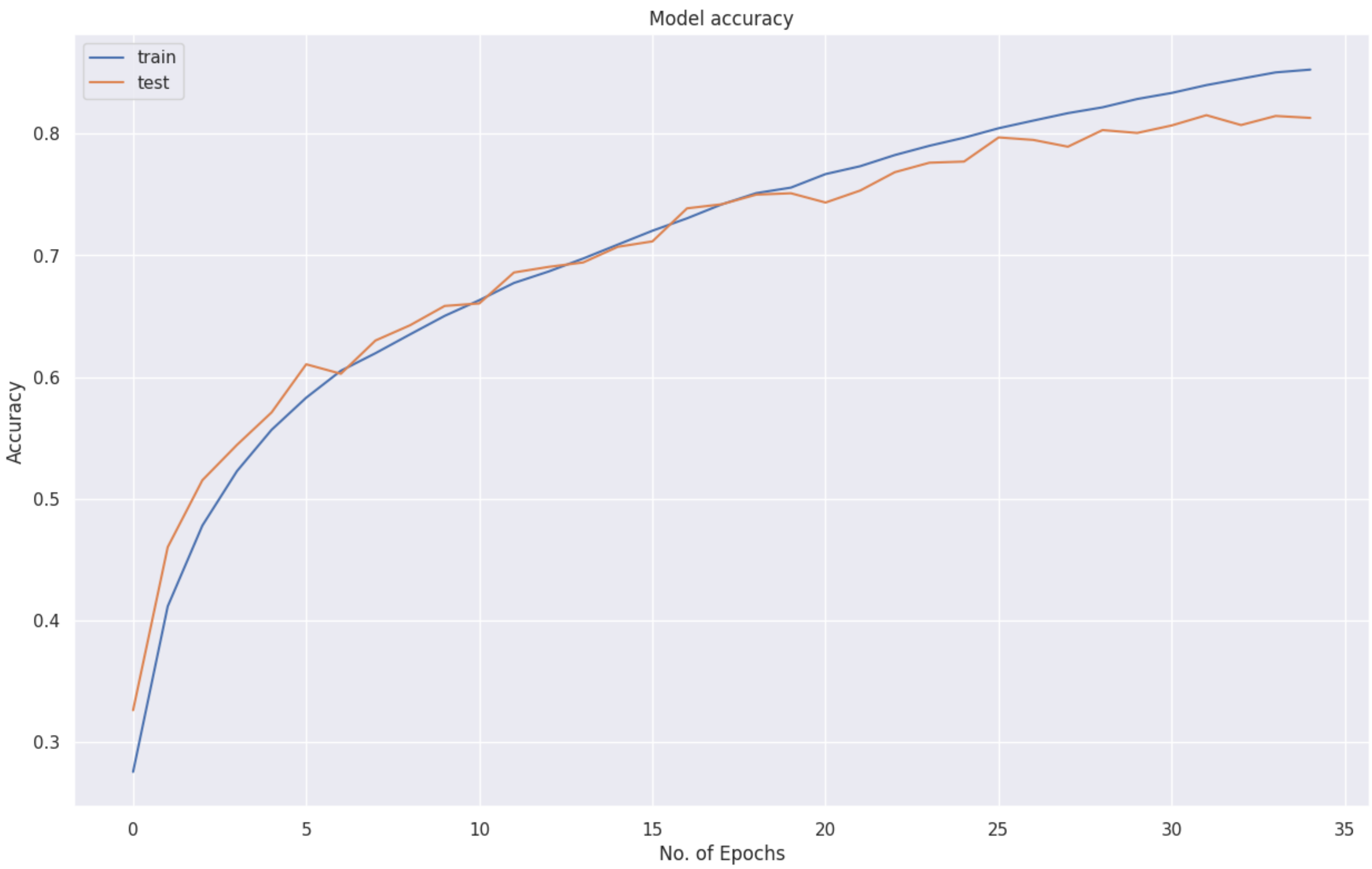
```
197/197 [==============================] - 1s 5ms/step - loss: 0.6056 - accuracy: 0.8131
Accuracy of our model on test data :  81.31256699562073 %
197/197 [==============================] - 1s 5ms/step - loss: 0.6056 - accuracy: 0.8131
```

```
Loss of our model on test data :  0.6056268811225891
```

The test accuracy & loss of our model is 81.31% & 0.605 respectively, which is better than many exsited state-of-the-art results.

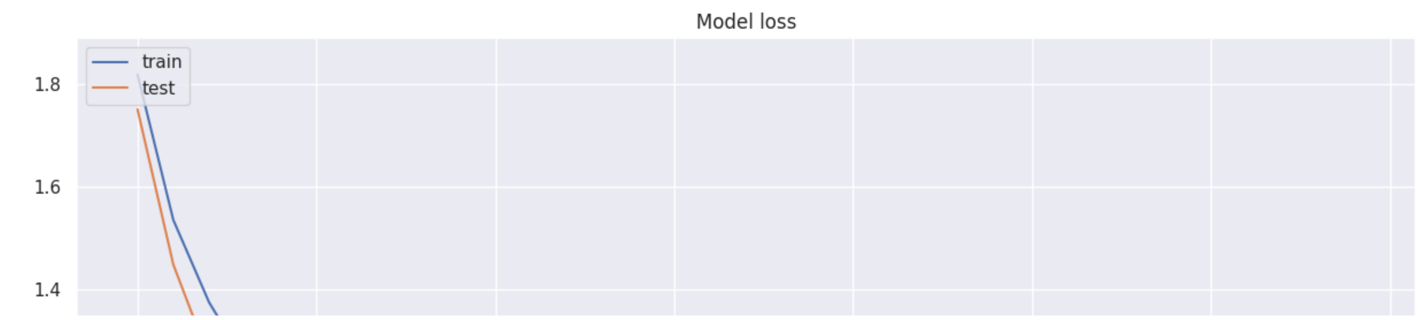
In [26]:

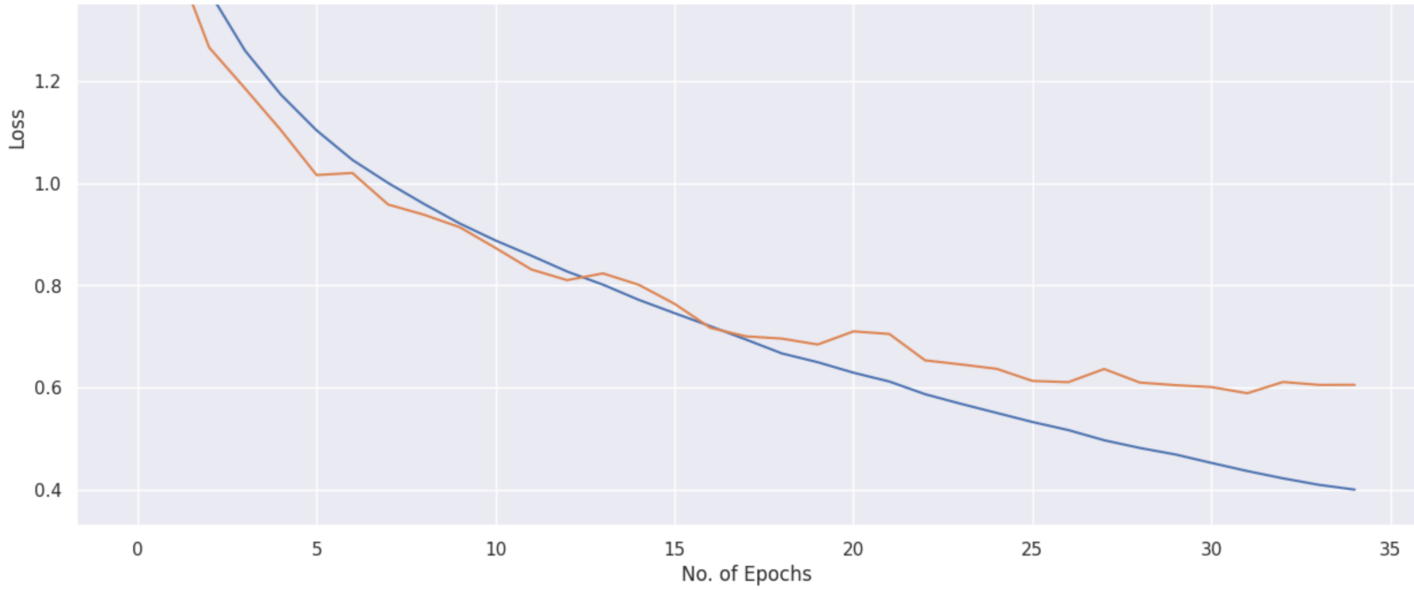
```
plt.figure(figsize=(15, 9))

# Summarize history for accuracy
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('No. of Epochs')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```



In [27]:

```
plt.figure(figsize=(15, 9))

# summarize history for loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('No. of Epochs')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```





7. Getting Classification Report & Plotting Confusion Matrix

In [28]:

```
# Making Predictio on Test Data
y_pred = model.predict(x_test)
y_result = []

for pred in y_pred:
    y_result.append(np.argmax(pred))
y_result[:10]
```

```
197/197 [==============================] - 1s 4ms/step
```

Out[28]:

```
[6, 5, 5, 6, 1, 0, 6, 4, 1, 6]
```

In [29]:

```
y_actual = []

for pred in y_test:
    y_actual.append(np.argmax(pred))
y_actual[:10]
```

Out[29]:

```
[6, 5, 5, 6, 1, 0, 3, 4, 1, 3]
```

In [30]:

```
# Getting Classification Report
from sklearn.metrics import confusion_matrix, classification_report
print(classification_report(y_actual, y_result))
```

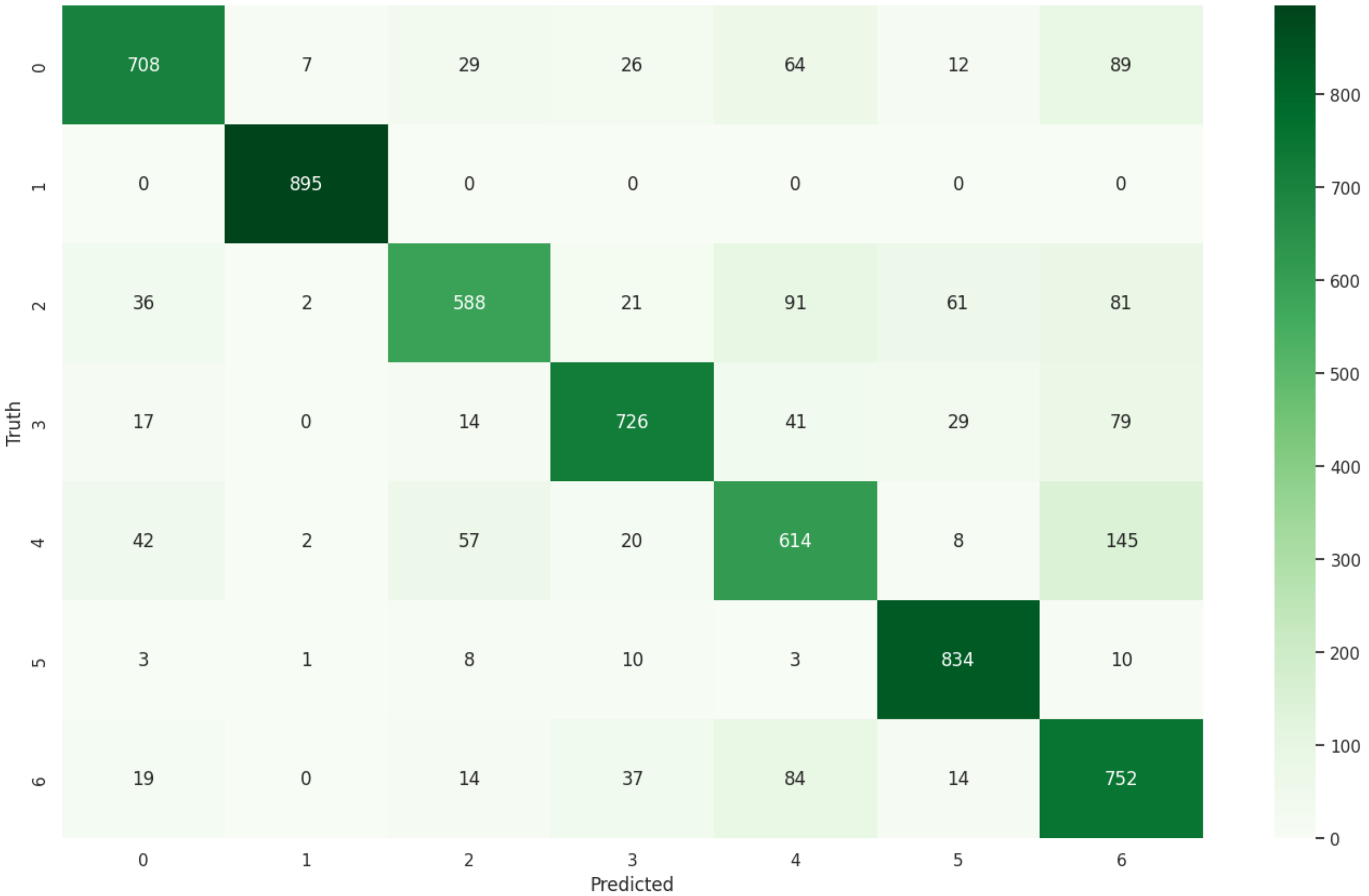
```
              precision    recall  f1-score   support

           0       0.86      0.76      0.80       935
           1       0.99      1.00      0.99       895
           2       0.83      0.67      0.74       880
           3       0.86      0.80      0.83       906
           4       0.68      0.69      0.69       888
           5       0.87      0.96      0.91       869
           6       0.65      0.82      0.72       920

    accuracy                           0.81      6293
   macro avg       0.82      0.81      0.81      6293
weighted avg       0.82      0.81      0.81      6293
```

In [32]:

```
cm = tf.math.confusion_matrix(labels = y_actual, predictions = y_result)

plt.figure(figsize = (17, 10))
sns.heatmap(cm, annot = True, fmt = 'd', cmap="Greens")
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

Out[32]:

```
Text(178.75, 0.5, 'Truth')
```



8. Save the Model

In [33]:

```
# Save the Model
model.save("/content/drive/MyDrive/Thesis Work - Facial Expression Detection & Recognitio
n using Deep Learning/Facial_Expression_Detection_System.hdf5")
```

In [42]:

```
#Saving the  model to  use it later on
fer_json = model.to_json()
with open("/content/drive/MyDrive/Thesis Work - Facial Expression Detection & Recognition
using Deep Learning/Facial Expression Recognition.json", "w") as json_file:
    json_file.write(fer_json)
model.save_weights("fer.h5")
```

9. Making Prediction in a Real-Time

In [ ]:

```
import os
import cv2
import numpy as np
```

```
from keras.models import model_from_json
from keras.preprocessing import image

#load model
model = model_from_json(open("/content/drive/MyDrive/Thesis Work - Facial Expression Dete
ction & Recognition using Deep Learning/Facial Expression Recognition.json", "r").read())
#load weights
model.load_weights('fer.h5')


face_haar_cascade = cv2.CascadeClassifier('/content/drive/MyDrive/Thesis Work - Facial Ex
pression Detection & Recognition using Deep Learning/haarcascade_frontalface_default.xml'
)


cap=cv2.VideoCapture(0)

while True:
    ret,test_img=cap.read()# captures frame and returns boolean value and captured image
    if not ret:
        continue
    gray_img= cv2.cvtColor(test_img, cv2.COLOR_BGR2GRAY)

    faces_detected = face_haar_cascade.detectMultiScale(gray_img, 1.32, 5)


    for (x,y,w,h) in faces_detected:
        cv2.rectangle(test_img,(x,y),(x+w,y+h),(255,0,0),thickness=7)
        roi_gray=gray_img[y:y+w,x:x+h]#cropping region of interest i.e. face area from
image
        roi_gray=cv2.resize(roi_gray,(48,48))
        img_pixels = image.img_to_array(roi_gray)
        img_pixels = np.expand_dims(img_pixels, axis = 0)
        img_pixels /= 255

        predictions = model.predict(img_pixels)

        #find max indexed array
        max_index = np.argmax(predictions[0])

        emotions = ('angry', 'disgust', 'fear', 'happy', 'sad', 'surprise', 'neutral')
        predicted_emotion = emotions[max_index]

        cv2.putText(test_img, predicted_emotion, (int(x), int(y)), cv2.FONT_HERSHEY_SIMP
LEX, 1, (0,0,255), 2)

    resized_img = cv2.resize(test_img, (1000, 700))
    cv2.imshow('Facial emotion analysis ',resized_img)



    if cv2.waitKey(10) == ord('q'):#wait until 'q' key is pressed
        break

cap.release()
cv2.destroyAllWindows()
```

In [ ]: