Name : Afaan Ansari

UICD : 2019230064

Batch : C

Sub : FCI

Detection of Emoji using facial expression

```
emotional recognition with the help of facial expressions. Today is the
era of fast and dynamic internet and communication technologies. Hence,
the communication is more convenient as compared to the past. Use of
communications through different channels, such as mobile phones and
computers, are very common in today's era. E-mails, text messaging, blog
entries, and comments are some of the forms of communication which are
very common today. To enhance the experience of communication, emojis were
developed . Emoji's are the pictorial representation of the facial
expression of human beings. They are very helpful in the facilitation of
human emotional experiences.

The Facial  emoji  recognizer detects  the  expression  of  the  person
and converts that expression of the person into the emoji of 7 classes .
We implement a classifier for face detection of  CNN algorithm for
expression  detection .
```

Dataset link [Facial expression (https://www.kaggle.com/c/challenges-in-representation-learning-facial-expression-recognition-challenge/data)](https://www.kaggle.com/c/challenges-in-representation-learning-facial-expression-recognition-challenge/data)

Github link [Emoji-detection-using-facial-expression (https://github.com/affan00733/Emoji-detection-using-facial-expression)](https://github.com/affan00733/Emoji-detection-using-facial-expression)

```
load the required modules
```

In [76]:
```
import pandas as pd
import numpy as np
from keras.models import load_model
import os.path
import cv2
from keras.models import Sequential
from keras.layers import Dense, Activation, Dropout, Flatten, BatchNormaliz
from keras.layers import Conv2D
from keras.utils import to_categorical
from keras.callbacks import ModelCheckpoint
from keras import callbacks
from keras.callbacks import EarlyStopping
from keras.layers import MaxPool2D
from keras.layers import Conv2D,MaxPooling2D
import matplotlib.pyplot as plt
from keras.applications.vgg16 import VGG16
from keras.initializers import glorot_normal,glorot_uniform, he_normal, he_
from keras.optimizers import Adamax,Adam, Adadelta, Adagrad, RMSprop, Nadam
from keras.callbacks import EarlyStopping
from keras.utils import to_categorical
from keras.regularizers import l2,l1
from keras.callbacks import ModelCheckpoint
import warnings
warnings.filterwarnings('ignore')
```

here is the type of the emoji's that we are going to classify , we classifing it into 7 categories

In [77]:
```
emoji = ['Angry','Disgust','Fear','Happy','Sad','Surprise','Neutral']
# 0=Angry, 1=Disgust, 2=Fear, 3=Happy, 4=Sad, 5=Surprise, 6=Neutral
```

Now we are reading the dataset csv file which is combind of training , validation and test set . and we have columns emotion which is output label , usage which gives the type of set and despite of giving the images it gives the image cell values which is pixel column

In [78]:
```
data = pd.read_csv("/kaggle/input/face-data-1/icml_face_data.csv")
data.columns = ['emotion', 'Usage', 'pixels']
```

here we are visulaizing the dataset in dataframe

In [79]:
```
data
```

Out[79]:

	emotion	Usage	pixels
0	0	Training	70 80 82 72 58 58 60 63 54 58 60 48 89 115 121...
1	0	Training	151 150 147 155 148 133 111 140 170 174 182 15...
2	2	Training	231 212 156 164 174 138 161 173 182 200 106 38...
3	4	Training	24 32 36 30 32 23 19 20 30 41 21 22 32 34 21 1...
4	6	Training	4 0 0 0 0 0 0 0 0 0 0 0 3 15 23 28 48 50 58 84...
...	...	...	...
35882	6	PrivateTest	50 36 17 22 23 29 33 39 34 37 37 37 39 43 48 5...
35883	3	PrivateTest	178 174 172 173 181 188 191 194 196 199 200 20...
35884	0	PrivateTest	17 17 16 23 28 22 19 17 25 26 20 24 31 19 27 9...
35885	3	PrivateTest	30 28 28 29 31 30 42 68 79 81 77 67 67 71 63 6...
35886	2	PrivateTest	19 13 14 12 13 16 21 33 50 57 71 84 97 108 122...

35887 rows × 3 columns

In [80]:
```
data["Usage"].unique()
```

Out[80]:
```
array(['Training', 'PublicTest', 'PrivateTest'], dtype=object)
```

now we have created the prepare data function here we are transforming the image pixels cell data into the format which is accepted by the neural network model which is row , columns , channes is 48 , 48 , 1 respectively . to transform it into 48x48 we are reshaping it and also dividing it by 255 as it is an image

In [81]:
```
def prepare_data(data):
    image_array = np.zeros(shape=(len(data), 48, 48, 1))
    image_label = np.array(list(map(int, data['emotion'])))

    for i, row in enumerate(data.index):
        image = np.fromstring(data.loc[row, 'pixels'], dtype=int, sep=' ')
        image = np.reshape(image, (48, 48))
        image_array[i, :, :, 0] = image / 255

    return image_array, image_label
```

now we are showing the distribution of training , validation and test set

In [82]:
```
full_train_images, full_train_labels = prepare_data(data[data['Usage']=='Tr
val_images, val_labels = prepare_data(data[data['Usage']=='PublicTest'])
test_images, test_labels = prepare_data(data[data['Usage']=='PrivateTest'])

print(full_train_images.shape)
print(full_train_labels.shape)
print(val_images.shape)
print(val_labels.shape)
print(test_images.shape)
print(test_labels.shape)
```

```
(28709, 48, 48, 1)
(28709,)
(3589, 48, 48, 1)
(3589,)
(3589, 48, 48, 1)
(3589,)
```

As to give the output Y label to the model we need to categorize it And we are categoring the training , validation and test set

In [83]:
```
y_train_ohe = to_categorical(full_train_labels, num_classes=7)
y_val_ohe = to_categorical(val_labels, num_classes=7)
y_test_ohe = to_categorical(test_labels, num_classes=7)
```

In [84]:
```
print(y_train_ohe.shape)
print(y_val_ohe.shape)
print(y_test_ohe.shape)
```

```
(28709, 7)
(3589, 7)
(3589, 7)
```

number of image rows and columns

In [85]:
```
img_rows=48
img_cols=48
```

now we are defing the model and doing the hyper-parameter tuning . we are making a block of CNN model where first 4 blocks is of the convolution layer and other remaining 3 blocks is of fully connected layer . And in each convolution block there is pair of convolution layer which is going from 32 , 64 , 128, 256 and filter of size 3x3 . Also we are using relu activation function for non-linearinty . as we are using blocks of convolution layer so we need to use batch normalization so they can be normalized into same scale . Also we are using the max pooling layer of pool size 2x2 and dropout rate of 20% for convolution layer blocks

And in the fully connected layer blocks first we are using the flatten layer so the input can be normalized and reshaped into the output format . Here also we are using relu activation function and batch normalization which has same purpose as above and we are changing the dropout rate to 50% . And conecting it to dense layer and at the last layer we are giveing the softmax activation function because it is multiclass prediction .

In [86]:
```
model = Sequential()

# Block-1

model.add(Conv2D(32,(3,3),padding='same',input_shape=(img_rows,img_cols,1)))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Conv2D(32,(3,3),padding='same',input_shape=(img_rows,img_cols,1)))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.2))

# Block-2

model.add(Conv2D(64,(3,3),padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Conv2D(64,(3,3),padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.2))

# Block-3

model.add(Conv2D(128,(3,3),padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Conv2D(128,(3,3),padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.2))

# Block-4

model.add(Conv2D(256,(3,3),padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Conv2D(256,(3,3),padding='same'))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.2))

# Block-5

model.add(Flatten())
model.add(Dense(64))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Dropout(0.5))

# Block-6
```

```
model.add(Dense(64))
model.add(Activation('relu'))
model.add(BatchNormalization())
model.add(Dropout(0.5))

# Block-7

model.add(Dense(7))
model.add(Activation('softmax'))

print(model.summary())
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_8 (Conv2D)            (None, 48, 48, 32)        320       
_________________________________________________________________
activation_11 (Activation)   (None, 48, 48, 32)        0         
_________________________________________________________________
batch_normalization_10 (Batc (None, 48, 48, 32)        128       
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 48, 48, 32)        9248      
_________________________________________________________________
activation_12 (Activation)   (None, 48, 48, 32)        0         
_________________________________________________________________
batch_normalization_11 (Batc (None, 48, 48, 32)        128       
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 24, 24, 32)        0         
_________________________________________________________________
dropout_6 (Dropout)          (None, 24, 24, 32)        0         
_________________________________________________________________
conv2d_10 (Conv2D)           (None, 24, 24, 64)        18496     
_________________________________________________________________
activation_13 (Activation)   (None, 24, 24, 64)        0         
_________________________________________________________________
batch_normalization_12 (Batc (None, 24, 24, 64)        256       
_________________________________________________________________
conv2d_11 (Conv2D)           (None, 24, 24, 64)        36928     
_________________________________________________________________
activation_14 (Activation)   (None, 24, 24, 64)        0         
_________________________________________________________________
batch_normalization_13 (Batc (None, 24, 24, 64)        256       
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 12, 12, 64)        0         
_________________________________________________________________
dropout_7 (Dropout)          (None, 12, 12, 64)        0         
_________________________________________________________________
conv2d_12 (Conv2D)           (None, 12, 12, 128)       73856     
_________________________________________________________________
activation_15 (Activation)   (None, 12, 12, 128)       0         
_________________________________________________________________
batch_normalization_14 (Batc (None, 12, 12, 128)       512       
_________________________________________________________________
conv2d_13 (Conv2D)           (None, 12, 12, 128)       147584    
_________________________________________________________________
activation_16 (Activation)   (None, 12, 12, 128)       0         
```

```
_________________________________________________________________
batch_normalization_15 (Batc (None, 12, 12, 128)       512       
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 6, 6, 128)         0         
_________________________________________________________________
dropout_8 (Dropout)          (None, 6, 6, 128)         0         
_________________________________________________________________
conv2d_14 (Conv2D)           (None, 6, 6, 256)         295168    
_________________________________________________________________
activation_17 (Activation)   (None, 6, 6, 256)         0         
_________________________________________________________________
batch_normalization_16 (Batc (None, 6, 6, 256)         1024      
_________________________________________________________________
conv2d_15 (Conv2D)           (None, 6, 6, 256)         590080    
_________________________________________________________________
activation_18 (Activation)   (None, 6, 6, 256)         0         
_________________________________________________________________
batch_normalization_17 (Batc (None, 6, 6, 256)         1024      
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 3, 3, 256)         0         
_________________________________________________________________
dropout_9 (Dropout)          (None, 3, 3, 256)         0         
_________________________________________________________________
flatten_1 (Flatten)          (None, 2304)              0         
_________________________________________________________________
dense_3 (Dense)              (None, 64)                147520    
_________________________________________________________________
activation_19 (Activation)   (None, 64)                0         
_________________________________________________________________
batch_normalization_18 (Batc (None, 64)                256       
_________________________________________________________________
dropout_10 (Dropout)         (None, 64)                0         
_________________________________________________________________
dense_4 (Dense)              (None, 64)                4160      
_________________________________________________________________
activation_20 (Activation)   (None, 64)                0         
_________________________________________________________________
batch_normalization_19 (Batc (None, 64)                256       
_________________________________________________________________
dropout_11 (Dropout)         (None, 64)                0         
_________________________________________________________________
dense_5 (Dense)              (None, 7)                 455       
_________________________________________________________________
activation_21 (Activation)   (None, 7)                 0         
=================================================================
Total params: 1,328,167
Trainable params: 1,325,991
Non-trainable params: 2,176
_________________________________________________________________
None
```

The more hyperparameters are model checkpoints which saves the model in every epochs which has the best result by monitoring the validation loss . Early stopping stops the model automatically is validation loss doesn't improves at the rate of 3 epochs and at last we are adding the reduce LR Plateau whcih helps to dynamically changing the learning rate , here we are monitoring the validation loss at rate of 3 epochs. And we using the categorical crossentropy as loss function as it is categorical classification , Adam optimizer we are using because it gives the momentum Also is takes long step from left to right and small step from top to bottom.

In [87]:
```
from keras.optimizers import RMSprop,SGD,Adam
from keras.callbacks import ModelCheckpoint, EarlyStopping, ReduceLROnPlate

checkpoint = ModelCheckpoint('emoji.h5',
                             monitor='val_loss',
                             mode='min',
                             save_best_only=True,
                             verbose=1)

earlystop = EarlyStopping(monitor='val_loss',
                          min_delta=0,
                          patience=3,
                          verbose=1,
                          restore_best_weights=True
                          )

reduce_lr = ReduceLROnPlateau(monitor='val_loss',
                              factor=0.2,
                              patience=3,
                              verbose=1,
                              min_delta=0.0001)

callbacks = [earlystop,checkpoint,reduce_lr]

model.compile(loss='categorical_crossentropy',
              optimizer = Adam(lr=0.001),
              metrics=['accuracy'])
```

Then we are training the model by giving training set and validation and giving callbacks and maximum 100 epochs

In [88]:
```
hist = model.fit(full_train_images, y_train_ohe, epochs=100, verbose=1,
          validation_data=(val_images, y_val_ohe), shuffle=True, callbacks=
```

```
Epoch 1/100
898/898 [==============================] - 39s 41ms/step - loss: 2.3590 -
accuracy: 0.1951 - val_loss: 1.6481 - val_accuracy: 0.3335

Epoch 00001: val_loss improved from inf to 1.64806, saving model to emoj
i.h5
Epoch 2/100
898/898 [==============================] - 37s 41ms/step - loss: 1.6708 -
accuracy: 0.3370 - val_loss: 1.3970 - val_accuracy: 0.4536

Epoch 00002: val_loss improved from 1.64806 to 1.39699, saving model to e
moji.h5
Epoch 3/100
898/898 [==============================] - 37s 41ms/step - loss: 1.4428 -
accuracy: 0.4411 - val_loss: 1.3036 - val_accuracy: 0.4921

Epoch 00003: val_loss improved from 1.39699 to 1.30358, saving model to e
moji.h5
Epoch 4/100
898/898 [==============================] - 37s 41ms/step - loss: 1.3514 -
accuracy: 0.4869 - val_loss: 1.2315 - val_accuracy: 0.5227

Epoch 00004: val_loss improved from 1.30358 to 1.23154, saving model to e
moji.h5
Epoch 5/100
898/898 [==============================] - 37s 41ms/step - loss: 1.2546 -
accuracy: 0.5315 - val_loss: 1.1694 - val_accuracy: 0.5528

Epoch 00005: val_loss improved from 1.23154 to 1.16936, saving model to e
moji.h5
Epoch 6/100
898/898 [==============================] - 37s 41ms/step - loss: 1.2031 -
accuracy: 0.5542 - val_loss: 1.1896 - val_accuracy: 0.5456

Epoch 00006: val_loss did not improve from 1.16936
Epoch 7/100
898/898 [==============================] - 36s 41ms/step - loss: 1.1493 -
accuracy: 0.5769 - val_loss: 1.2132 - val_accuracy: 0.5372

Epoch 00007: val_loss did not improve from 1.16936
Epoch 8/100
898/898 [==============================] - 36s 41ms/step - loss: 1.0905 -
accuracy: 0.5999 - val_loss: 1.1422 - val_accuracy: 0.5740

Epoch 00008: val_loss improved from 1.16936 to 1.14217, saving model to e
moji.h5
Epoch 9/100
898/898 [==============================] - 36s 41ms/step - loss: 1.0681 -
accuracy: 0.6143 - val_loss: 1.0756 - val_accuracy: 0.5949

Epoch 00009: val_loss improved from 1.14217 to 1.07557, saving model to e
moji.h5
```

```
Epoch 10/100
898/898 [==============================] - 36s 41ms/step - loss: 1.0120 -
accuracy: 0.6307 - val_loss: 1.0963 - val_accuracy: 0.5893

Epoch 00010: val_loss did not improve from 1.07557
Epoch 11/100
898/898 [==============================] - 36s 41ms/step - loss: 0.9605 -
accuracy: 0.6515 - val_loss: 1.0375 - val_accuracy: 0.6141

Epoch 00011: val_loss improved from 1.07557 to 1.03747, saving model to e
moji.h5
Epoch 12/100
898/898 [==============================] - 36s 40ms/step - loss: 0.9100 -
accuracy: 0.6737 - val_loss: 1.0199 - val_accuracy: 0.6280

Epoch 00012: val_loss improved from 1.03747 to 1.01990, saving model to e
moji.h5
Epoch 13/100
898/898 [==============================] - 36s 40ms/step - loss: 0.8682 -
accuracy: 0.6908 - val_loss: 1.0564 - val_accuracy: 0.6130

Epoch 00013: val_loss did not improve from 1.01990
Epoch 14/100
898/898 [==============================] - 36s 40ms/step - loss: 0.8113 -
accuracy: 0.7122 - val_loss: 1.0627 - val_accuracy: 0.6272

Epoch 00014: val_loss did not improve from 1.01990
Epoch 15/100
898/898 [==============================] - 36s 40ms/step - loss: 0.7684 -
accuracy: 0.7297 - val_loss: 1.0484 - val_accuracy: 0.6303
Restoring model weights from the end of the best epoch.

Epoch 00015: val_loss did not improve from 1.01990

Epoch 00015: ReduceLROnPlateau reducing learning rate to 0.00020000000949
949026.
Epoch 00015: early stopping
```

now we evaluating the model by test set which gives the 63 % accuracy

In [89]:
```
# training loss and accuracy
train_acc = hist.history['accuracy']
val_acc = hist.history['val_accuracy']
print('Training Accuracy: ', train_acc[-1])
print('Validation Accuracy: ', val_acc[-1])

# test loss and accuracy
score, acc = model.evaluate(test_images, y_test_ohe)
print('Test score:', score)
print('Test accuracy:', acc)
```

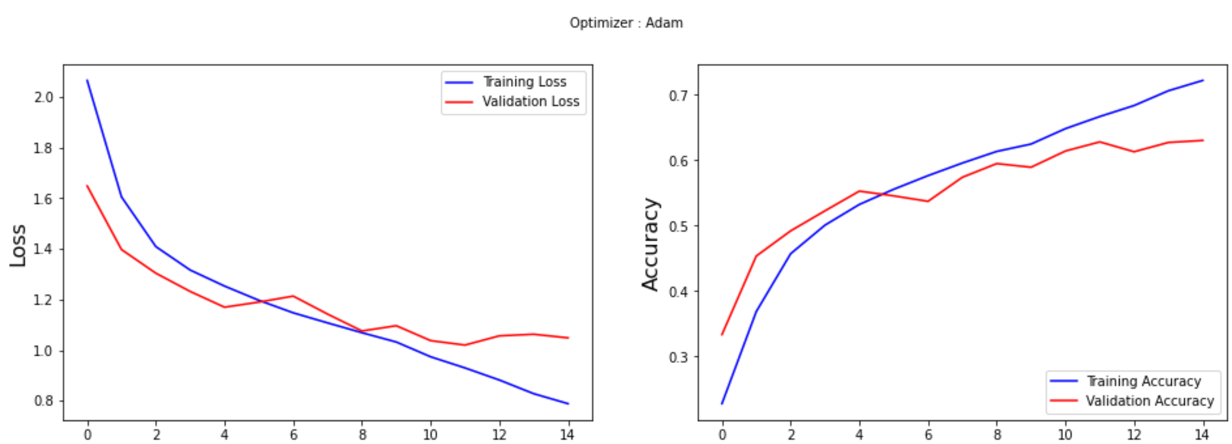
```
Training Accuracy:  0.7219687104225159
Validation Accuracy:  0.630259096622467
113/113 [==============================] - 4s 32ms/step - loss: 0.9804 -
accuracy: 0.6305
Test score: 0.9803521037101746
Test accuracy: 0.630537748336792
```

now by visualiztion we can see that the gap between training and validation accuracy and training and validation loss is less in the below graph so it is not overfitting

In [90]:
```

plt.figure(figsize=(16,5))
# training loss graph
plt.subplot(1, 2, 1)
plt.suptitle('Optimizer : Adam', fontsize=10)
plt.ylabel('Loss', fontsize=16)
plt.plot(hist.history['loss'], color='b', label='Training Loss')
plt.plot(hist.history['val_loss'], color='r', label='Validation Loss')
plt.legend(loc='upper right')

# training accuracy graph
plt.subplot(1, 2, 2)
plt.ylabel('Accuracy', fontsize=16)
plt.plot(hist.history['accuracy'], color='b', label='Training Accuracy')
plt.plot(hist.history['val_accuracy'], color='r', label='Validation Accurac
plt.legend(loc='lower right')
plt.show()
```



Now we predicting the output emojis in test set

In [91]:
```
test_res = model.predict(test_images)
```

In [92]:
```
test_res = np.argmax(test_res,axis=1)
```

Transforming output label to emojis in tes tset

In [93]:
```
res_final = pd.DataFrame()
res_final["pixels"] = data["pixels"][data['Usage']=='PrivateTest']
res_final["emoji"] = test_res
res_final.loc[res_final.emoji == 0, "emoji"] = "😡 "
res_final.loc[res_final.emoji == 1, "emoji"] = "🤢 "
res_final.loc[res_final.emoji == 2, "emoji"] = "😰 "
res_final.loc[res_final.emoji == 3, "emoji"] = "😁 "
res_final.loc[res_final.emoji == 4, "emoji"] = "😥 "
res_final.loc[res_final.emoji == 5, "emoji"] = "😱 "
res_final.loc[res_final.emoji == 6, "emoji"] = "😀 "
res_final = res_final.reset_index()
```

Visulaizing the emojis in test set as dataframe

In [94]:
```
res_final
```

Out[94]:

	index	pixels	emoji
0	32298	170 118 101 88 88 75 78 82 66 74 68 59 63 64 6...	😡
1	32299	7 5 8 6 7 3 2 6 5 4 4 5 7 5 5 5 6 7 7 7 10 10 ...	😥
2	32300	232 240 241 239 237 235 246 117 24 24 22 13 12...	😰
3	32301	200 197 149 139 156 89 111 58 62 95 113 117 11...	😥
4	32302	40 28 33 56 45 33 31 78 152 194 200 186 196 20...	😱
...	...	...	...
3584	35882	50 36 17 22 23 29 33 39 34 37 37 37 39 43 48 5...	😀
3585	35883	178 174 172 173 181 188 191 194 196 199 200 20...	😁
3586	35884	17 17 16 23 28 22 19 17 25 26 20 24 31 19 27 9...	😥
3587	35885	30 28 28 29 31 30 42 68 79 81 77 67 67 71 63 6...	😁
3588	35886	19 13 14 12 13 16 21 33 50 57 71 84 97 108 122...	😥

3589 rows × 3 columns

Transforming output label to emojis in validation set

In [96]:
```
val_test = pd.DataFrame()
val_test = data[data['Usage']=='PublicTest']
val_test.loc[val_test.emotion == 0, "emoji"] = "😡 "
val_test.loc[val_test.emotion == 1, "emoji"] = "🤢 "
val_test.loc[val_test.emotion == 2, "emoji"] = "😨 "
val_test.loc[val_test.emotion == 3, "emoji"] = "😁 "
val_test.loc[val_test.emotion == 4, "emoji"] = "😥 "
val_test.loc[val_test.emotion == 5, "emoji"] = "😱 "
val_test.loc[val_test.emotion == 6, "emoji"] = "😀 "
val_test = val_test.reset_index()
```

Visulaizing the emojis in validation set as dataframe

In [97]:
```
val_test
```

Out[97]:

	index	emotion	Usage	pixels	emoji
0	28709	0	PublicTest	254 254 254 254 254 249 255 160 2 58 53 70 77 ...	😡
1	28710	1	PublicTest	156 184 198 202 204 207 210 212 213 214 215 21...	🤢
2	28711	4	PublicTest	69 118 61 60 96 121 103 87 103 88 70 90 115 12...	😥
3	28712	6	PublicTest	205 203 236 157 83 158 120 116 94 86 155 180 2...	😀
4	28713	3	PublicTest	87 79 74 66 74 96 77 80 80 84 83 89 102 91 84 ...	😁
...	...	...	...	...	...
3584	32293	4	PublicTest	178 176 172 173 173 174 176 173 166 166 206 22...	😥
3585	32294	3	PublicTest	25 34 42 44 42 47 57 59 59 58 54 51 50 56 63 6...	😁
3586	32295	4	PublicTest	255 255 255 255 255 255 255 255 255 255 255 25...	😥
3587	32296	4	PublicTest	33 25 31 36 36 42 69 103 132 163 175 183 187 1...	😥
3588	32297	4	PublicTest	61 63 59 75 151 159 166 161 143 170 127 131 18...	😥

3589 rows × 5 columns

Transforming output label to emojis in training set

In [98]:
```
training = pd.DataFrame()
training = data[data['Usage']=='Training']
training.loc[training.emotion == 0, "emoji"] = "😡 "
training.loc[training.emotion == 1, "emoji"] = "🤢 "
training.loc[training.emotion == 2, "emoji"] = "😨 "
training.loc[training.emotion == 3, "emoji"] = "😁 "
training.loc[training.emotion == 4, "emoji"] = "😥 "
training.loc[training.emotion == 5, "emoji"] = "😱 "
training.loc[training.emotion == 6, "emoji"] = "😀 "
training = training.reset_index()
```

Visulaizing the emojis in training set as dataframe

In [99]:
```
training
```

Out[99]:

	index	emotion	Usage	pixels	emoji
0	0	0	Training	70 80 82 72 58 58 60 63 54 58 60 48 89 115 121...	😡
1	1	0	Training	151 150 147 155 148 133 111 140 170 174 182 15...	😡
2	2	2	Training	231 212 156 164 174 138 161 173 182 200 106 38...	😨
3	3	4	Training	24 32 36 30 32 23 19 20 30 41 21 22 32 34 21 1...	😥
4	4	6	Training	4 0 0 0 0 0 0 0 0 0 0 0 3 15 23 28 48 50 58 84...	😀
...	...	...	...	...	...
28704	28704	2	Training	84 85 85 85 85 85 85 85 86 86 86 87 86 86 91 9...	😨
28705	28705	0	Training	114 112 113 113 111 111 112 113 115 113 114 11...	😡
28706	28706	4	Training	74 81 87 89 95 100 98 93 105 120 127 133 146 1...	😥
28707	28707	0	Training	222 227 203 90 86 90 84 77 94 87 99 119 134 14...	😡
28708	28708	4	Training	195 199 205 206 205 203 206 209 208 210 212 21...	😥

28709 rows × 5 columns

Now we are defing the function so we can see the images and the predicted emojis for the training , validationa and test set

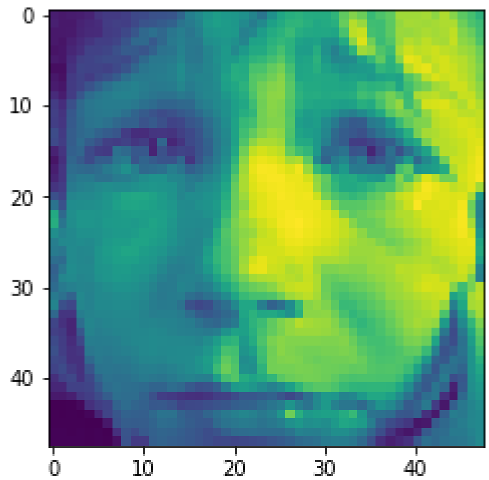
In [100]:
```
def predict_training(index):
    print(training.emoji[index])
    plt.imshow(full_train_images[index])
```

In [101]:
```
def predict_validation(index):
    print(val_test.emoji[index])
    plt.imshow(val_images[index])
```

In [102]:
```
def predict_test(index):
    print(res_final.emoji[index])
    plt.imshow(test_images[index])
```

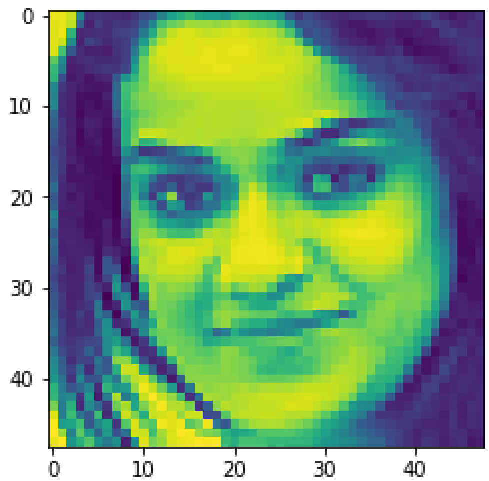
predicted emoji for training which is sad face emoji

In [107]:
```
predict_training(6)
```



predicted emoji for validation which is happy face emoji

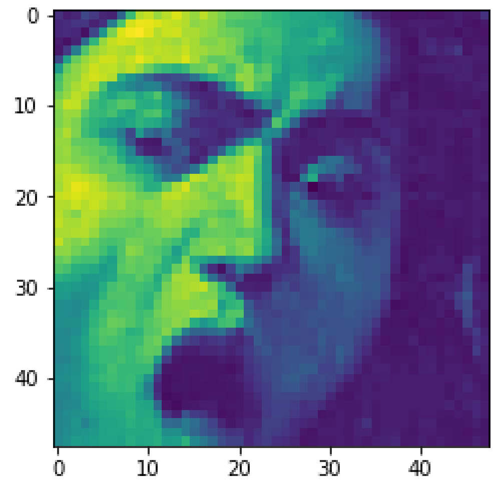
In [108]:
```
predict_validation(5)
```



predicted emoji for test which is shocking face emoji

In [109]:
```
predict_test(4)
```

😱



Conclusion

- In this project we have done Emoji detection using facial expression
- We have made a block of CNN model which the input we have transpormed into 48 , 48 , 1 . where 48 is rows and columns and 1 is channel.
- The result we get from this model is 71% training accuracy , 64% validation accuracy anf 63% testing accuracy
- The hyper-parameter tuning we have used is model checkpoints for saving best model , eary stopping for automatically stopping the model if it is not improving and reduceLR for dynamically changing learning rate
- The above shown graph we can see the gap between training and validation accuracy and training and validation loss is less so it is not overfitting
- There are some images of training , validation and testing are shown above with their emojis by comparison we can see that we are getting promising result