Emotion Detection from Images using Machine Learning

Introduction:

In human communications, facial expressions contain critical nonverbal information that can provide additional clues and meanings to verbal communications. Some studies have suggested that 60–80% of communication is nonverbal. This nonverbal information includes facial expressions, eye contact, tones of voice, hand gestures and physical distancing. In particular, facial expression analysis has become a popular research topic.

Problem Statement:

Our aim is to develope a Machine Learning model that is capable of detecting the emotion from the face in the input image.

How machine learning can be used to solve this problem?

Here, our input is Image data and the output is single label indicating the corresponding emotion. We can use the existing image data to make Machine Learning model learn the underlying relationship between the input images and output class label.

Once the model learns this relationship, we can use it to predict the corresponding emotion from the person's face in the input image.

Literature Survey:

To understand the Problem Statement thoroughly and to learn various possible approaches, following research papers and/or blogs were referred.

1. https://www.sciencedirect.com/science/article/pii/S1877050920318019
2. https://edps.europa.eu/system/files/2021-05/21-05-26_techdispatch-facial-emotion-recognition_ref_en.pdf
3. https://arxiv.org/pdf/1804.08348.pdf
4. https://www.robots.ox.ac.uk/~vgg/publications/2015/Parkhi15/parkhi15.pdf

Necessary Libraries

```
# Importing Necessary Libraries
import warnings
warnings.filterwarnings('ignore')
import gdown
import os
import numpy as np
import pandas as pd
```

```
import seaborn as sns
import matplotlib.pyplot as plt
import seaborn as sns
import cv2
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
from sklearn.metrics import f1_score
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.preprocessing import OneHotEncoder
import tensorflow as tf
from tensorflow.keras import Input
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.callbacks import ModelCheckpoint
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.callbacks import ReduceLROnPlateau
from tensorflow.keras.callbacks import TensorBoard
from tensorflow.keras.layers import Flatten, Conv2D, GlobalAveragePooling2D
from tensorflow.keras.layers import MaxPooling2D, AveragePooling2D, Flatten
from tensorflow.keras.layers import Dropout, BatchNormalization, Activation
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications import VGG19

RANDOM_SEED = 111
```

Performance Metrics:

Since it is a Multi Class Clasiification problem, following Metrics can be used to monitor and compare performance of various ML models and best performing model can be selected.

1. Accuracy (https://scikit-learn.org/stable/modules/generated/sklearn.metrics.accuracy_score.html#sklearn.metrics.accuracy_score)
2. Weighted_F1_score (https://scikit-learn.org/stable/modules/generated/sklearn.metrics.f1_score.html#sklearn.metrics.f1_score)
3. Confusion Matrix (https://scikit-learn.org/stable/modules/generated/sklearn.metrics.confusion_matrix.html)

About Dataset:

Data Source: https://www.kaggle.com/datasets/ashishpatel26/facial-expression-recognitionferchallenge/data

Data is zipped in single archive.zip file and has size 96.59 MB.

Archive.zip can be unzipped into the following folder structure

```
archive.zip
       |
       |--- Submission.csv(7.01KB)
       |
       |--- fer2013
                |
                |---fer2013
                        |
                        |--- README(476 B)
                        |--- fer2013.bib(1.36 KB)
                        |--- fer2013.csv(287.13 MB)
```

File fer2013.csv contains the image pixel values and the corresponding class labels.

Download and Read the data

```
# Downloading data using gdown
!gdown 1pKOyT-wtAyNHAe6966BbFBQnNK5arll4
```

```
Downloading...
From: https://drive.google.com/uc?id=1pKOyT-wtAyNHAe6966BbFBQnNK5arll4
To: /content/archive.zip
100% 101M/101M [00:01<00:00, 88.7MB/s]
```

```
# Extracting archive.zip file
```

```
# Extracting archive.zip file
!unzip /content/archive.zip
```

```
Archive:  /content/archive.zip
  inflating: Submission.csv
  inflating: fer2013/fer2013/README
  inflating: fer2013/fer2013/fer2013.bib
  inflating: fer2013/fer2013/fer2013.csv
```

```
# Reading the data
data_df = pd.read_csv('/content/fer2013/fer2013/fer2013.csv')
data_df.head()
```

	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 3 15 23 28 48 50 58 84...	Training

Exploring the data

```
# Check data size
data_df.shape
```

```
(35887, 3)
```

```
# Check image size
sample = data_df['pixels'][0]
pixels_length = len(sample.split())
img_size = np.sqrt(pixels_length)
print(f"Each image is of size {img_size} * {img_size}")
```

```
Each image is of size 48.0 * 48.0
```

```
# Data info
data_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 35887 entries, 0 to 35886
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   emotion  35887 non-null  int64
 1   pixels   35887 non-null  object
 2   Usage    35887 non-null  object
dtypes: int64(1), object(2)
memory usage: 841.2+ KB
```

```
# Check null values
data_df.isnull().sum()
```

```
emotion    0
pixels     0
Usage      0
dtype: int64
```

```
# Check duplicates
print(f"Duplicate values count: {data_df.duplicated().sum()}")
```

```
Duplicate values count: 1234
```

```
# Drop duplicates
data_df.drop_duplicates(keep='first', inplace=True)
```

```
# Data size after dropping duplicates
data_df.shape
```

```
(34653, 3)
```

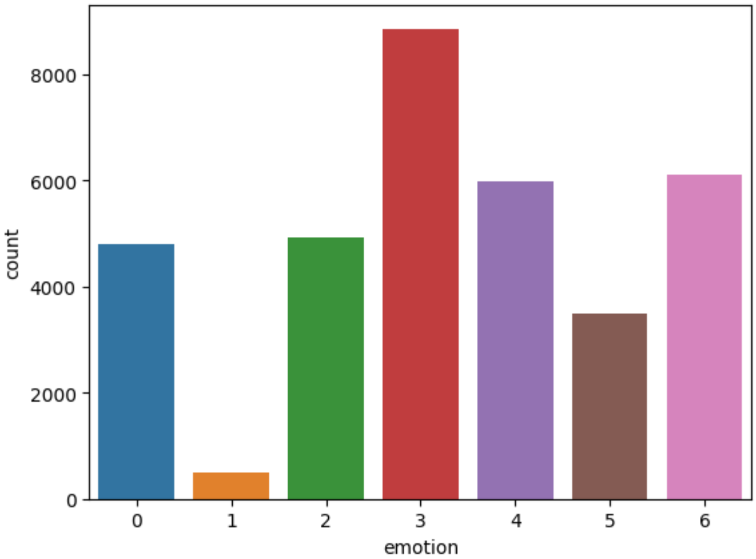
```
# Unique class labels
u = np.unique(data_df['emotion'])
print(f"There are {len(u)} unique emotions {u}")
```

```
There are 7 unique emotions [0 1 2 3 4 5 6]
```

```
#Text to numerical labeling
emotions_labels = {0:'anger', 1:'disgust', 2:'fear', 3:'happiness', 4: 'sadness', 5: 'surprise', 6: 'neutral'}
emotion_list = list(emotions_labels.values())
```

```
# Emotions distribution
sns.countplot(x=data_df['emotion'])
data_df['emotion'].value_counts()
```

```
3    8859
6    6105
4    5977
2    4925
0    4800
5    3496
1     491
Name: emotion, dtype: int64
```



Observation(s):

1. fer2013.csv file contains 3 columns emotion, pixels, Usage

```
*   emotion -> id of the enotion
*   pixels -> flattened array of pixel values in the image
*   Usage -> string indicating training or test image
```

2. Data contains 35887 images with corresponding class labels.
3. There are 1234 duplicate images which are dropped to get 34653 unique images
4. There are no null values in the dataset
5. There are 7 unique emotions

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

6. Emotions distibution in imbalanced with only 491 unique images for 'disgust' emotion, all other emotions have at least 3400 images.

Viewing Sample Images

```
#Viewing the images
fig = plt.figure(1, (12, 12))
k = 0
for label in sorted(data_df.emotion.unique()):
    for j in range(7):
        px = data_df[data_df.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, cmap = 'gray')
        ax.set_xticks([])
        ax.set_yticks([])
        ax.set_title(emotions_labels[label])
        plt.tight_layout()
```

Pre-processing Data for Model Training

Data preparation for ML Models

Here we will split the pixels value string into individual pixel value columns. This pre processing will help us in training ML Classification models and Deep MLP models.

```
# Copying df
ml_data_df = data_df.copy()

# Drop unwanted columns
ml_data_df = ml_data_df.drop('Usage', axis=1)
ml_data_df.columns
```

```
Index(['emotion', 'pixels'], dtype='object')
```

```
# Splitting pixel string and creating separate column for each pixel value
new_cols = list(range(0, 2304))
ml_data_df[new_cols] = data_df['pixels'].str.split(' ', expand=True)
ml_data_df = ml_data_df.drop('pixels', axis=1)
ml_data_df.head()
```

	emotion	0	1	2	3	4	5	6	7	8	...	2294	2295	2296	2297	2298	2299	2300	2301	2302	2303
0	0	70	80	82	72	58	58	60	63	54	...	159	182	183	136	106	116	95	106	109	82
1	0	151	150	147	155	148	133	111	140	170	...	105	108	95	108	102	67	171	193	183	184
2	2	231	212	156	164	174	138	161	173	182	...	104	138	152	122	114	101	97	88	110	152
3	4	24	32	36	30	32	23	19	20	30	...	174	126	132	132	133	136	139	142	143	142
4	6	4	0	0	0	0	0	0	0	0	...	12	34	31	31	31	27	31	30	29	30

5 rows × 2305 columns

```
with open('ml_data_df.csv', mode='w') as f:
    ml_data_df.to_csv(f)
```

Data Preparation for DL Models

Here we will convert the pixels value strings into 2d image array and further into rgb image which can be used to train CNN models.

```
# Split pixel values and convert to 2d array
img_array = data_df['pixels'].apply(lambda x: np.array(x.split(' ')).reshape(48, 48).astype('float32'))
img_array = np.stack(img_array, axis = 0)
img_array.shape
```

```
(34653, 48, 48)
```

```
# Converting image arrays to rgb images
img_data = []

for i in range(len(img_array)):
    img = cv2.cvtColor(img_array[i], cv2.COLOR_GRAY2RGB)
    img_data.append(img)

img_data = np.array(img_data)
print(img_data.shape)
```

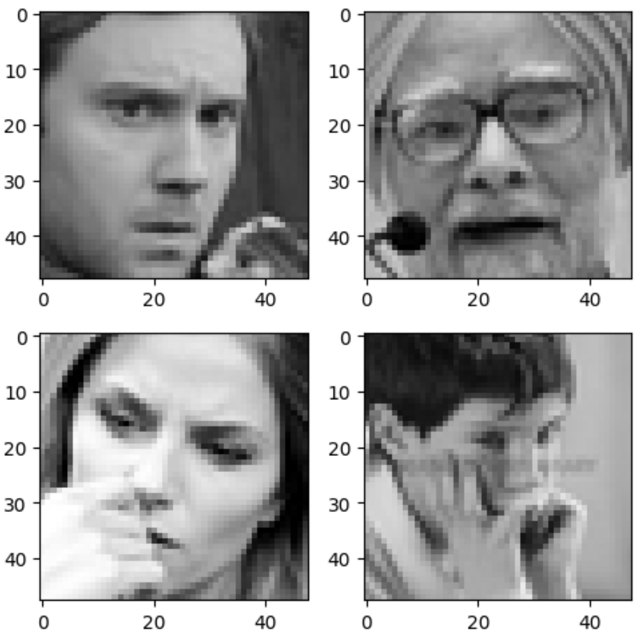
```
(34653, 48, 48, 3)
```

```
# Saving img_data array
with open('image_data.npy', mode='wb') as f:
    np.save(f, img_data)
```

```
# Saving labels array
labels = np.array(data_df['emotion'].values)

with open('labels.npy', mode='wb') as f:
    np.save(f, labels)
```

```
# View processed rgb image samples
fig = plt.figure(1, (5, 5))
k = 1
```

```

for i in range(4):
    img = img_data[i].astype(np.uint8)
    plt.subplot(2,2,k)
    plt.imshow(img)
    plt.tight_layout()
    k+=1
```



Modelling Approaches

Many different modelling experiments can be carried out in order to achieve the best performance for our classification task. Here we will experiment with 5 such approaches.

1. Multi Class Classification using SVM
2. Deep Multi-Layer Perceptron
3. Custom CNN Model
4. Transfer Learning using Pretrained CNN Model
5. Training State of the art CNN Model from scratch.

Defining custom function for model evaluation

```
def print_evaluation_metrics(true, pred, data_name:str):
    '''
    Evaluates accuracy score, weighted f1 score and plots confusion matrix for given true and predicted labels
    '''
    print('* *' * 25)
    # Accuracy
    acc = accuracy_score(true, pred)
    print(f"{data_name} data accuracy score: {acc}")
    # weighted f1 score
    f1 = f1_score(true, pred, average='weighted')
    print(f"{data_name} data weighted f1 score: {f1}")
    # Confusion matrix
    cmat = confusion_matrix(true, pred)
    plt.figure(figsize=(6,4))
    sns.heatmap(cmat, annot=True, fmt='02d', cmap="YlGnBu",xticklabels=emotion_list,
                yticklabels=emotion_list)
    plt.title(f'{data_name} data confusion matrix')
    plt.show()
```

```
def plot_metrics(history):
    '''
    Plots accuracy vs epoch and loss vs epoch plots for NN training.
    '''
    fig = plt.figure(figsize=(12, 4))
```

```
    ax = plt.subplot(1, 2, 1)
    sns.lineplot(x=history.epoch, y=history.history['accuracy'], label='train')
    sns.lineplot(x=history.epoch, y=history.history['val_accuracy'], label='valid')
    plt.title('Accuracy Vs Epoch')

    ax = plt.subplot(1, 2, 2)
    sns.lineplot(x=history.epoch, y=history.history['loss'], label='train')
    sns.lineplot(x=history.epoch, y=history.history['val_loss'], label='valid')
    plt.title('Loss Vs Epoch')

    plt.tight_layout()
    plt.show()
```

1. Multi Class Classification using SVM

Train-Cross_Validation-Test Split

```
# Separating pixels and class labels
y = ml_data_df['emotion']
X = ml_data_df.drop('emotion', axis=1)
```

```
# Train Test Split (80-20 split)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify=y, random_state=RANDOM_SEED)

# Train CV Split (80-10 split)
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.1, stratify=y_train, random_state=RAND

# Shapes
print(f'X_train shape: {X_train.shape}')
print(f'X_cv shape:    {X_cv.shape}')
print(f'X_test shape:  {X_test.shape}')
print(f'y_train shape: {y_train.shape}')
print(f'y_cv shape:    {y_cv.shape}')
print(f'y_test shape:  {y_test.shape}')
```

```
X_train shape: (24949, 2304)
X_cv shape:    (2773, 2304)
X_test shape:  (6931, 2304)
y_train shape: (24949,)
y_cv shape:    (2773,)
y_test shape:  (6931,)
```

Normalizing Data

```
# Min-Max Normalization
pixel_normalizer = MinMaxScaler()
pixel_normalizer.fit(X_train)

X_train_norm = pixel_normalizer.transform(X_train)
X_cv_norm = pixel_normalizer.transform(X_cv)
X_test_norm = pixel_normalizer.transform(X_test)
```

Model Training

```
# Params
kernel = 'rbf'
c = 1.0
```

```
# Base SVC Model
svm_rbf = SVC(C=c, kernel=kernel, degree=3)

# Train model
svm_rbf.fit(X_train_norm,y_train)
```

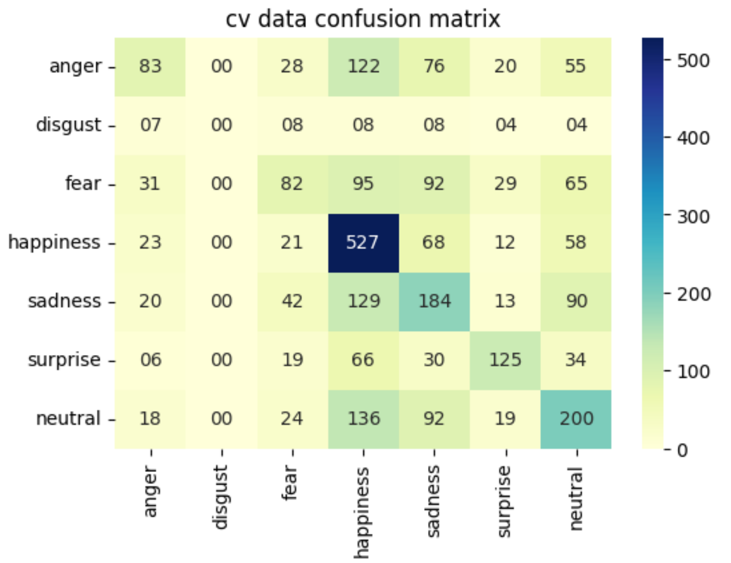
```
▾ SVC
SVC()
```

```
# Predictions
X_train_pred = svm_rbf.predict(X_train_norm)
X_cv_pred = svm_rbf.predict(X_cv_norm)
X_test_pred = svm_rbf.predict(X_test_norm)
```

```
# Check Model performance
print_evaluation_metrics(y_train, X_train_pred, 'train')
print_evaluation_metrics(y_cv, X_cv_pred, 'cv')
```

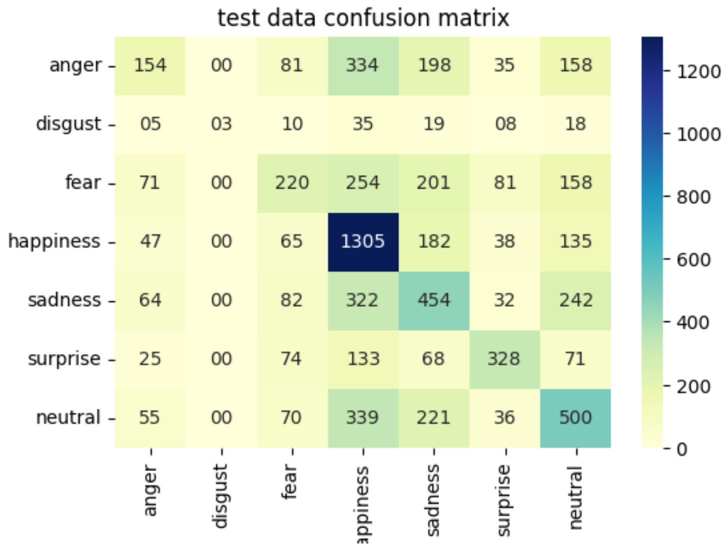
```
* ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** *
train data accuracy score: 0.6085614653893944
train data weighted f1 score: 0.5957275885795638
```


```
* ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** *
cv data accuracy score: 0.43310494049765597
cv data weighted f1 score: 0.4111602800742764
```




```
# Model performance on test data
print_evaluation_metrics(y_test, X_test_pred, 'test')
print(classification_report(y_test, X_test_pred))
```

```
* ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** *
test data accuracy score: 0.42764391862646084
test data weighted f1 score: 0.40433925845207547
```



2. Deep Multi Layer Perceptron

```
0       0.37      0.16      0.22       960
```

Train-Test Split

```
3       0.48      0.74      0.58      1772
```

```
# Separating pixels and class labels
y = ml_data_df['emotion']
X = ml_data_df.drop('emotion', axis=1)
```

```
macro avg       0.50      0.34      0.35      6931
```

```
# Train Test Split (80-20 split)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify=y, random_state=RANDOM_SEED)

# Train CV Split (80-10 split)
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.1, stratify=y_train, random_state=RAND(

# Shapes
print(f'X_train shape: {X_train.shape}')
print(f'X_cv shape:    {X_cv.shape}')
print(f'X_test shape:  {X_test.shape}')
print(f'y_train shape: {y_train.shape}')
print(f'y_cv shape:    {y_cv.shape}')
print(f'y_test shape:  {y_test.shape}')
```

```
X_train shape: (24949, 2304)
X_cv shape:    (2773, 2304)
X_test shape:  (6931, 2304)
y_train shape: (24949,)
y_cv shape:    (2773,)
y_test shape:  (6931,)
```

Normalize pixel data

```
# Min-Max Normalization
pixel_normalizer = MinMaxScaler()
pixel_normalizer.fit(X_train)

X_train_norm = pixel_normalizer.transform(X_train)
X_cv_norm = pixel_normalizer.transform(X_cv)
X_test_norm = pixel_normalizer.transform(X_test)
```

Encode class labels

```
# Encode class labels
ohe = OneHotEncoder()
ohe.fit(np.array(y_train).reshape(-1, 1))

y_train_enc = ohe.transform(np.array(y_train).reshape(-1,1)).todense()
y_cv_enc = ohe.transform(np.array(y_cv).reshape(-1,1)).todense()
y_test_enc = ohe.transform(np.array(y_test).reshape(-1,1)).todense()
```

```

# Shapes
print(f'y_train_enc shape: {y_train_enc.shape}')
print(f'y_cv_enc shape: {y_cv_enc.shape}')
print(f'y_test_enc shape: {y_test_enc.shape}')
```

```
y_train_enc shape: (24949, 7)
y_cv_enc shape: (2773, 7)
y_test_enc shape: (6931, 7)
```

Define MLP Network

```
# Defining MLP Model using tensorflow
mlp_model = tf.keras.Sequential()
mlp_model.add(Input(shape=(2304)))
mlp_model.add(Dense(512, activation='relu'))
mlp_model.add(Dropout(0.2))
mlp_model.add(Dense(256, activation='relu'))
mlp_model.add(Dropout(0.2))
mlp_model.add(Dense(128, activation='relu'))
mlp_model.add(Dense(64, activation='relu'))
mlp_model.add(Dense(16, activation='relu'))
mlp_model.add(Dense(7, activation='softmax'))

# Summary
mlp_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 512)               1180160

 dropout (Dropout)           (None, 512)               0

 dense_1 (Dense)             (None, 256)               131328

 dropout_1 (Dropout)         (None, 256)               0

 dense_2 (Dense)             (None, 128)               32896

 dense_3 (Dense)             (None, 64)                8256

 dense_4 (Dense)             (None, 16)                1040

 dense_5 (Dense)             (None, 7)                 119

=================================================================
Total params: 1353799 (5.16 MB)
Trainable params: 1353799 (5.16 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Define Callbacks

```
# Create necessary directories
os.makedirs('mlp/models', exist_ok=True)
os.makedirs('mlp/logs', exist_ok=True)
```

```
# Callbacks
saver = ModelCheckpoint('/content/mlp/models_{epoch:02d}.hdf5', monitor='val_loss', verbose=1, save_best_only=True)
stopper = EarlyStopping(monitor='val_loss', patience=7, restore_best_weights=True, verbose=1)
reducer = ReduceLROnPlateau(monitor='val_loss', factor=0.05, patience=5, verbose=1)
tb = TensorBoard(log_dir='/content/mlp/logs', histogram_freq=1)

callbacks = [saver, stopper, reducer, tb]
```

Train Model

```
# Params
optimizer = 'Adam'
loss = 'categorical_crossentropy'
metrics = ['accuracy']
batch_size = 8
epochs = 100
```

```
1 # Compile Model
2 mlp_model.compile(optimizer=optimizer, loss=loss, metrics=metrics)
```

```
1 # Train Model
2 mlp_history = mlp_model.fit(X_train_norm, y_train_enc, batch_size=batch_size, epochs=epochs,
3                             callbacks=callbacks, validation_data=[X_cv_norm, y_cv_enc])
```

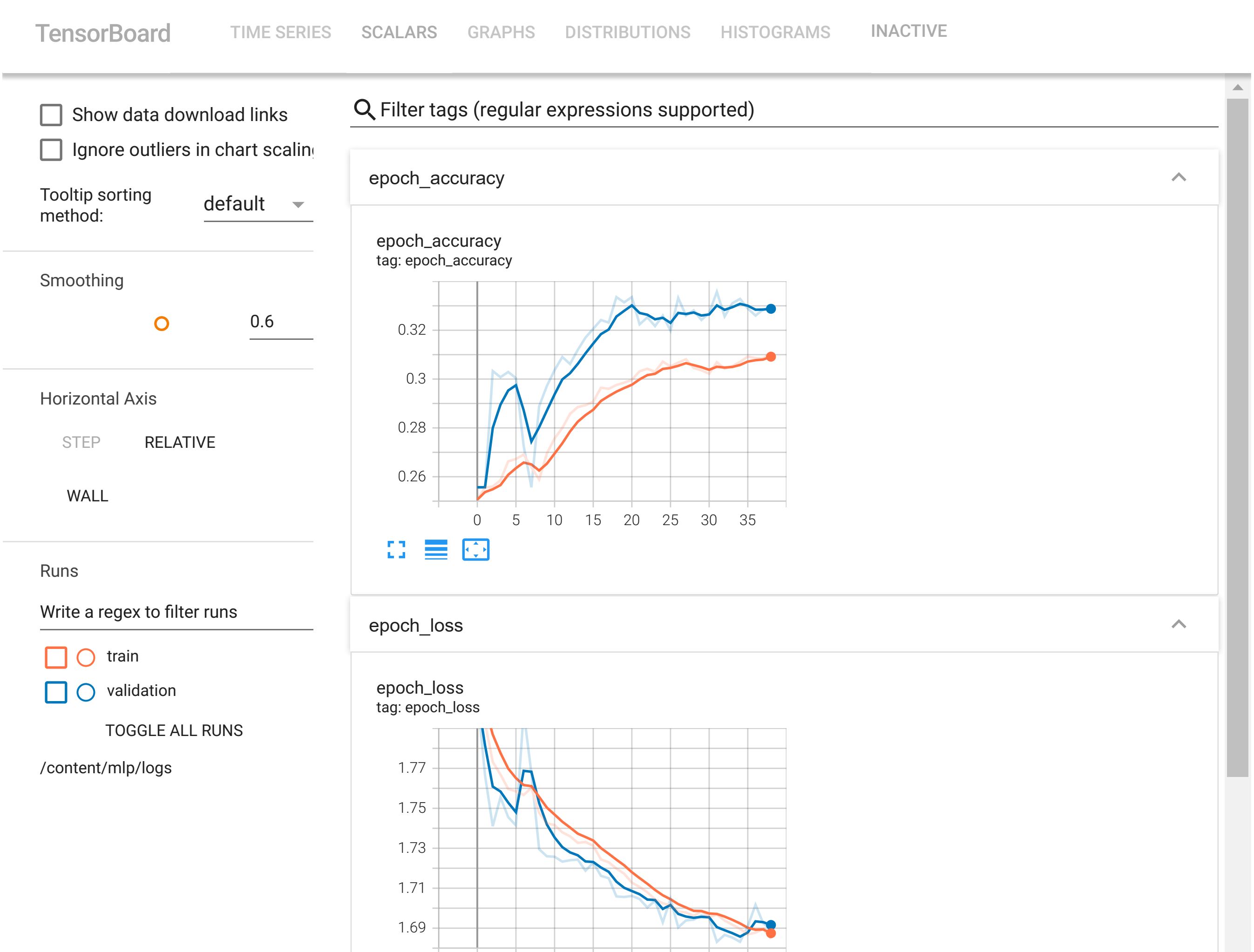
```
3119/3119 [==============================] - 12s 4ms/step - loss: 1.7015 - accuracy: 0.3052 - val_loss: 1.7046 - val_accuracy: 0
Epoch 27/100
3118/3119 [============================>.] - ETA: 0s - loss: 1.6983 - accuracy: 0.3068
Epoch 27: val_loss improved from 1.69292 to 1.69040, saving model to /content/mlp/models_27.hdf5
3119/3119 [==============================] - 12s 4ms/step - loss: 1.6983 - accuracy: 0.3067 - val_loss: 1.6904 - val_accuracy: 0
Epoch 28/100
3106/3119 [============================>.] - ETA: 0s - loss: 1.6976 - accuracy: 0.3082
Epoch 28: val_loss did not improve from 1.69040
3119/3119 [==============================] - 12s 4ms/step - loss: 1.6978 - accuracy: 0.3081 - val_loss: 1.6939 - val_accuracy: 0
Epoch 29/100
3108/3119 [============================>.] - ETA: 0s - loss: 1.6961 - accuracy: 0.3045
Epoch 29: val_loss did not improve from 1.69040
3119/3119 [==============================] - 12s 4ms/step - loss: 1.6962 - accuracy: 0.3045 - val_loss: 1.6942 - val_accuracy: 0
Epoch 30/100
3111/3119 [============================>.] - ETA: 0s - loss: 1.6986 - accuracy: 0.3035
Epoch 30: val_loss did not improve from 1.69040
3119/3119 [==============================] - 12s 4ms/step - loss: 1.6984 - accuracy: 0.3036 - val_loss: 1.6964 - val_accuracy: 0
Epoch 31/100
3114/3119 [============================>.] - ETA: 0s - loss: 1.6954 - accuracy: 0.3023
Epoch 31: val_loss did not improve from 1.69040
3119/3119 [==============================] - 12s 4ms/step - loss: 1.6955 - accuracy: 0.3022 - val_loss: 1.6951 - val_accuracy: 0
Epoch 32/100
3115/3119 [============================>.] - ETA: 0s - loss: 1.6970 - accuracy: 0.3068
Epoch 32: val_loss improved from 1.69040 to 1.68313, saving model to /content/mlp/models_32.hdf5
3119/3119 [==============================] - 12s 4ms/step - loss: 1.6968 - accuracy: 0.3069 - val_loss: 1.6831 - val_accuracy: 0
Epoch 33/100
3105/3119 [============================>.] - ETA: 0s - loss: 1.6940 - accuracy: 0.3043
Epoch 33: val_loss did not improve from 1.68313
3119/3119 [==============================] - 12s 4ms/step - loss: 1.6938 - accuracy: 0.3042 - val_loss: 1.6866 - val_accuracy: 0
Epoch 34/100
3117/3119 [============================>.] - ETA: 0s - loss: 1.6918 - accuracy: 0.3053
Epoch 34: val_loss did not improve from 1.68313
3119/3119 [==============================] - 12s 4ms/step - loss: 1.6917 - accuracy: 0.3053 - val_loss: 1.6853 - val_accuracy: 0
Epoch 35/100
3111/3119 [============================>.] - ETA: 0s - loss: 1.6896 - accuracy: 0.3071
Epoch 35: val_loss did not improve from 1.68313
3119/3119 [==============================] - 12s 4ms/step - loss: 1.6897 - accuracy: 0.3070 - val_loss: 1.6832 - val_accuracy: 0
Epoch 36/100
3114/3119 [============================>.] - ETA: 0s - loss: 1.6869 - accuracy: 0.3091
Epoch 36: val_loss did not improve from 1.68313
3119/3119 [==============================] - 12s 4ms/step - loss: 1.6869 - accuracy: 0.3093 - val_loss: 1.6909 - val_accuracy: 0
Epoch 37/100
3107/3119 [============================>.] - ETA: 0s - loss: 1.6880 - accuracy: 0.3085
Epoch 37: val_loss did not improve from 1.68313

Epoch 37: ReduceLROnPlateau reducing learning rate to 2.5000001187436284e-06.
3119/3119 [==============================] - 12s 4ms/step - loss: 1.6877 - accuracy: 0.3085 - val_loss: 1.7018 - val_accuracy: 0
Epoch 38/100
3117/3119 [============================>.] - ETA: 0s - loss: 1.6896 - accuracy: 0.3085
Epoch 38: val_loss did not improve from 1.68313
3119/3119 [==============================] - 12s 4ms/step - loss: 1.6896 - accuracy: 0.3084 - val_loss: 1.6924 - val_accuracy: 0
Epoch 39/100
3113/3119 [============================>.] - ETA: 0s - loss: 1.6849 - accuracy: 0.3109
Epoch 39: val_loss did not improve from 1.68313
Restoring model weights from the end of the best epoch: 32.
3119/3119 [==============================] - 12s 4ms/step - loss: 1.6847 - accuracy: 0.3109 - val_loss: 1.6895 - val_accuracy: 0
Epoch 39: early stopping
```

Model Performance Metrics

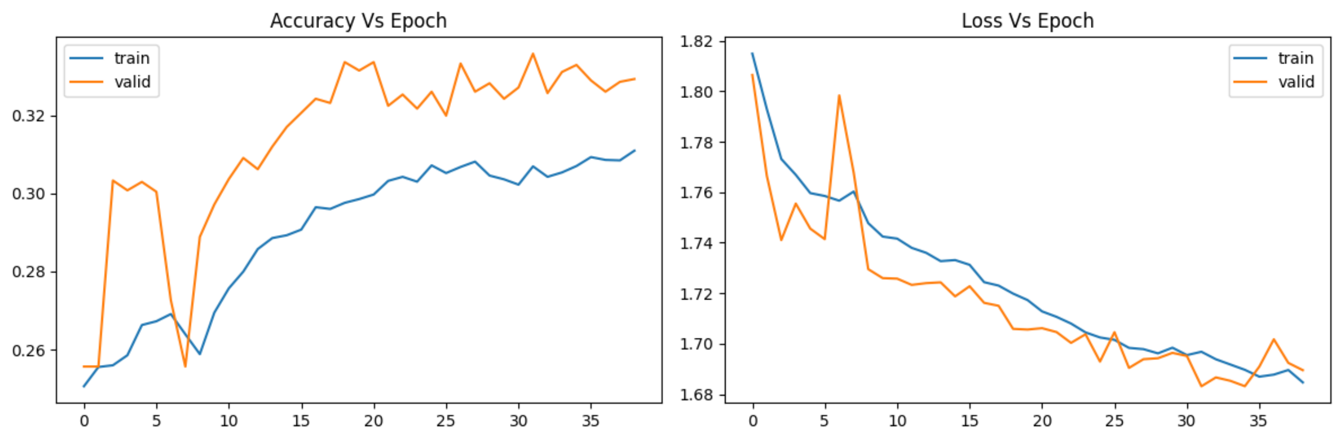
```
1 # Predictions
2 train_pred = np.argmax(mlp_model.predict(X_train_norm), axis=1)
3 cv_pred = np.argmax(mlp_model.predict(X_cv_norm), axis=1)
4 test_pred = np.argmax(mlp_model.predict(X_test_norm), axis=1)
```

```
780/780 [==============================] - 1s 1ms/step
87/87 [==============================] - 0s 1ms/step
217/217 [==============================] - 0s 1ms/step
```

```
1 # Tensorboard
2 %load_ext tensorboard
3 %tensorboard --logdir /content/mlp/logs
```



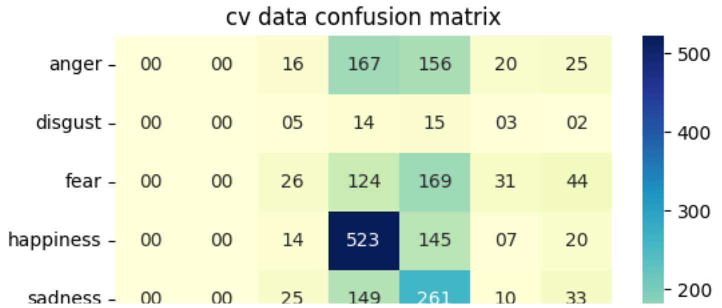

```
1 # Training Metrics
2 plot_metrics(mlp_history)
```




```
1 # Metrics
2 print_evaluation_metrics(y_train, train_pred, 'train')
3 print_evaluation_metrics(y_cv, cv_pred, 'cv')
```

```
* ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** *
train data accuracy score: 0.3419776343741232
train data weighted f1 score: 0.27628898043110894
```


```
* ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** *
cv data accuracy score: 0.33573746844572666
cv data weighted f1 score: 0.2677314866452974
```




```
1 # Test Data Performance
2 print_evaluation_metrics(y_test, test_pred, 'test')
3 print(classification_report(y_test, test_pred))
```

```
* ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** *
test data accuracy score: 0.32823546385802915
test data weighted f1 score: 0.264818713353675
```

3. Custom CNN Model

Train Test Split

```
# Train Test Split (80-20 split)
X_train, X_test, y_train, y_test = train_test_split(img_data, labels, test_size=0.2, stratify=labels, random_state=R/

# Train CV Split (80-10 split)
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.1, stratify=y_train, random_state=RAND(

# Shapes
print(f'X_train shape: {X_train.shape}')
print(f'X_cv shape:    {X_cv.shape}')
print(f'X_test shape:  {X_test.shape}')
print(f'y_train shape: {y_train.shape}')
print(f'y_cv shape:    {y_cv.shape}')
print(f'y_test shape:  {y_test.shape}')
```

```
X_train shape: (24949, 48, 48, 3)
X_cv shape:    (2773, 48, 48, 3)
X_test shape:  (6931, 48, 48, 3)
y_train shape: (24949,)
y_cv shape:    (2773,)
y_test shape:  (6931,)
          4       0.24      0.52      0.33      1196
```

Encode class labels

```
# Encode class labels
ohe = OneHotEncoder()
ohe.fit(np.array(y_train).reshape(-1, 1))

y_train_enc = ohe.transform(np.array(y_train).reshape(-1,1)).todense()
y_cv_enc = ohe.transform(np.array(y_cv).reshape(-1,1)).todense()
y_test_enc = ohe.transform(np.array(y_test).reshape(-1,1)).todense()

# Shapes
print(f'y_train_enc shape: {y_train_enc.shape}')
print(f'y_cv_enc shape: {y_cv_enc.shape}')
print(f'y_test_enc shape: {y_test_enc.shape}')
```

```
y_train_enc shape: (24949, 7)
y_cv_enc shape: (2773, 7)
y_test_enc shape: (6931, 7)
```

Define Custom CNN Network

```
# Define custom CNN Model

# Input Layer
input = Input(shape=(48,48,3), name='image_input')

# First Conv Block
x = Conv2D(256, kernel_size=3)(input)
x = MaxPooling2D()(x)
x = Dropout(0.2)(x)

# Second Conv Block
x = Conv2D(128, kernel_size=2)(x)
x = AveragePooling2D()(x)
x = Dropout(0.2)(x)

# Third Conv Block
x = Conv2D(64, kernel_size=3)(x)
x = AveragePooling2D()(x)
x = Dropout(0.2)(x)

# Flatten
x = Flatten()(x)

```

```
# Dense Layers
x = Dense(128, activation='relu')(x)
x = BatchNormalization()(x)
x = Dense(64, activation='relu')(x)
x = Dense(16, activation='relu')(x)

# Output Layer
output = Dense(7, activation='softmax')(x)

# Model
cnn_model = tf.keras.Model(inputs=input, outputs=output, name='custom_cnn')
cnn_model.summary()
```

```
Model: "custom_cnn"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 image_input (InputLayer)    [(None, 48, 48, 3)]       0

 conv2d (Conv2D)             (None, 46, 46, 256)       7168

 max_pooling2d (MaxPooling2  (None, 23, 23, 256)       0
 D)

 dropout_2 (Dropout)         (None, 23, 23, 256)       0

 conv2d_1 (Conv2D)           (None, 22, 22, 128)       131200

 average_pooling2d (Average  (None, 11, 11, 128)       0
 Pooling2D)

 dropout_3 (Dropout)         (None, 11, 11, 128)       0

 conv2d_2 (Conv2D)           (None, 9, 9, 64)          73792

 average_pooling2d_1 (Avera  (None, 4, 4, 64)          0
 gePooling2D)

 dropout_4 (Dropout)         (None, 4, 4, 64)          0

 flatten (Flatten)           (None, 1024)              0

 dense_6 (Dense)             (None, 128)               131200

 batch_normalization (Batch  (None, 128)               512
 Normalization)

 dense_7 (Dense)             (None, 64)                8256

 dense_8 (Dense)             (None, 16)                1040

 dense_9 (Dense)             (None, 7)                 119

=================================================================
Total params: 353287 (1.35 MB)
Trainable params: 353031 (1.35 MB)
Non-trainable params: 256 (1.00 KB)
_________________________________________________________________
```

Data Augmentation

```
# Define Data Generator
image_datagen = ImageDataGenerator(rescale=1./255,
                                   rotation_range = 15,
                                   width_shift_range = 0.15,
                                   height_shift_range = 0.15,
                                   shear_range = 0.15,
                                   zoom_range = 0.15,
                                   horizontal_flip = True,)
image_datagen.fit(X_train)
```

Callbacks

```
# Create necessary directories
os.makedirs('custom_cnn/models', exist_ok=True)
os.makedirs('custom_cnn/logs', exist_ok=True)
```

```
# Callbacks
saver = ModelCheckpoint('/content/custom_cnn/models_{epoch:02d}.hdf5', monitor='val_loss', verbose=1, save_best_only
```

```
stopper = EarlyStopping(monitor='val_loss', patience=7, restore_best_weights=True, verbose=1)
reducer = ReduceLROnPlateau(monitor='val_loss', factor=0.05, patience=5, verbose=1)
tb = TensorBoard(log_dir='/content/custom_cnn/logs', histogram_freq=1)

callbacks = [saver, stopper, reducer, tb]
```

Model Training

```
# Params
optimizer = 'Adam'
loss = 'categorical_crossentropy'
metrics = ['accuracy']
batch_size = 8
epochs = 100
```

```
# Compile Model
cnn_model.compile(optimizer=optimizer, loss=loss, metrics=metrics)
```

```
# Train Model
cnn_history = cnn_model.fit(image_datagen.flow(X_train, y_train_enc, batch_size = batch_size),
                                        validation_data = image_datagen.flow(X_cv, y_cv_enc, batch_size = 8),
                                        steps_per_epoch = len(X_train) / batch_size,
                                        epochs = epochs,
                                        callbacks = callbacks)
```

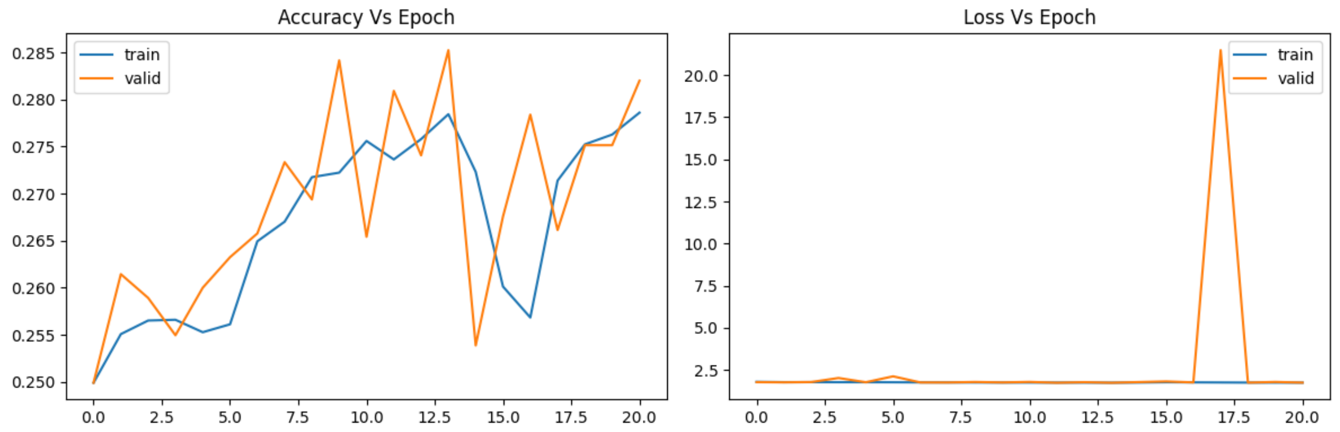
```
Epoch 1/100
3119/3118 [==============================] - ETA: 0s - loss: 1.8006 - accuracy: 0.2499
Epoch 1: val_loss improved from inf to 1.78282, saving model to /content/custom_cnn/models_01.hdf5
3118/3118 [==============================] - 41s 10ms/step - loss: 1.8006 - accuracy: 0.2499 - val_loss: 1.7828 - val_accuracy:
Epoch 2/100
3115/3118 [============================>.] - ETA: 0s - loss: 1.7815 - accuracy: 0.2552
Epoch 2: val_loss improved from 1.78282 to 1.77289, saving model to /content/custom_cnn/models_02.hdf5
3118/3118 [==============================] - 34s 11ms/step - loss: 1.7815 - accuracy: 0.2551 - val_loss: 1.7729 - val_accuracy:
Epoch 3/100
3118/3118 [============================>.] - ETA: 0s - loss: 1.7839 - accuracy: 0.2565
Epoch 3: val_loss did not improve from 1.77289
3118/3118 [==============================] - 33s 10ms/step - loss: 1.7839 - accuracy: 0.2565 - val_loss: 1.7886 - val_accuracy:
Epoch 4/100
3117/3118 [============================>.] - ETA: 0s - loss: 1.7800 - accuracy: 0.2566
Epoch 4: val_loss did not improve from 1.77289
3118/3118 [==============================] - 31s 10ms/step - loss: 1.7799 - accuracy: 0.2566 - val_loss: 2.0289 - val_accuracy:
Epoch 5/100
3119/3118 [==============================] - ETA: 0s - loss: 1.7802 - accuracy: 0.2553
Epoch 5: val_loss did not improve from 1.77289
3118/3118 [==============================] - 31s 10ms/step - loss: 1.7802 - accuracy: 0.2553 - val_loss: 1.7780 - val_accuracy:
Epoch 6/100
3117/3118 [============================>.] - ETA: 0s - loss: 1.7767 - accuracy: 0.2562
Epoch 6: val_loss did not improve from 1.77289
3118/3118 [==============================] - 31s 10ms/step - loss: 1.7767 - accuracy: 0.2561 - val_loss: 2.1281 - val_accuracy:
Epoch 7/100
3115/3118 [============================>.] - ETA: 0s - loss: 1.7697 - accuracy: 0.2646
Epoch 7: val_loss improved from 1.77289 to 1.76514, saving model to /content/custom_cnn/models_07.hdf5
3118/3118 [==============================] - 31s 10ms/step - loss: 1.7695 - accuracy: 0.2649 - val_loss: 1.7651 - val_accuracy:
Epoch 8/100
3117/3118 [============================>.] - ETA: 0s - loss: 1.7668 - accuracy: 0.2670
Epoch 8: val_loss improved from 1.76514 to 1.76309, saving model to /content/custom_cnn/models_08.hdf5
3118/3118 [==============================] - 31s 10ms/step - loss: 1.7668 - accuracy: 0.2670 - val_loss: 1.7631 - val_accuracy:
Epoch 9/100
3119/3118 [==============================] - ETA: 0s - loss: 1.7644 - accuracy: 0.2718
Epoch 9: val_loss did not improve from 1.76309
3118/3118 [==============================] - 31s 10ms/step - loss: 1.7644 - accuracy: 0.2718 - val_loss: 1.7924 - val_accuracy:
Epoch 10/100
3115/3118 [============================>.] - ETA: 0s - loss: 1.7600 - accuracy: 0.2724
Epoch 10: val_loss did not improve from 1.76309
3118/3118 [==============================] - 31s 10ms/step - loss: 1.7601 - accuracy: 0.2722 - val_loss: 1.7653 - val_accuracy:
Epoch 11/100
3119/3118 [==============================] - ETA: 0s - loss: 1.7594 - accuracy: 0.2756
Epoch 11: val_loss did not improve from 1.76309
3118/3118 [==============================] - 31s 10ms/step - loss: 1.7594 - accuracy: 0.2756 - val_loss: 1.7960 - val_accuracy:
Epoch 12/100
3114/3118 [============================>.] - ETA: 0s - loss: 1.7574 - accuracy: 0.2736
Epoch 12: val_loss improved from 1.76309 to 1.74655, saving model to /content/custom_cnn/models_12.hdf5
3118/3118 [==============================] - 31s 10ms/step - loss: 1.7574 - accuracy: 0.2736 - val_loss: 1.7465 - val_accuracy:
Epoch 13/100
3118/3118 [============================>.] - ETA: 0s - loss: 1.7571 - accuracy: 0.2757
Epoch 13: val_loss did not improve from 1.74655
3118/3118 [==============================] - 31s 10ms/step - loss: 1.7572 - accuracy: 0.2758 - val_loss: 1.7813 - val_accuracy:
Epoch 14/100
3118/3118 [============================>.] - ETA: 0s - loss: 1.7513 - accuracy: 0.2784
Epoch 14: val_loss improved from 1.74655 to 1.74604, saving model to /content/custom_cnn/models_14.hdf5
3118/3118 [==============================] - 31s 10ms/step - loss: 1.7512 - accuracy: 0.2784 - val_loss: 1.7460 - val_accuracy:
Epoch 15/100
```

Model Performace Metrics

```
# Predictions
train_pred = np.argmax(cnn_model.predict(X_train*1./255), axis=1)
cv_pred = np.argmax(cnn_model.predict(X_cv*1./255), axis=1)
test_pred = np.argmax(cnn_model.predict(X_test*1./255), axis=1)
```

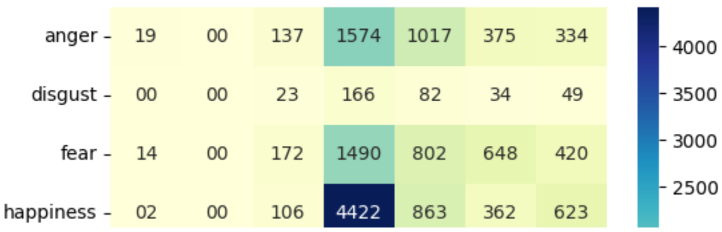
```
780/780 [==============================] - 3s 4ms/step
87/87 [==============================] - 0s 4ms/step
217/217 [==============================] - 1s 4ms/step
```

```
# Training Metrics
plot_metrics(cnn_history)
```



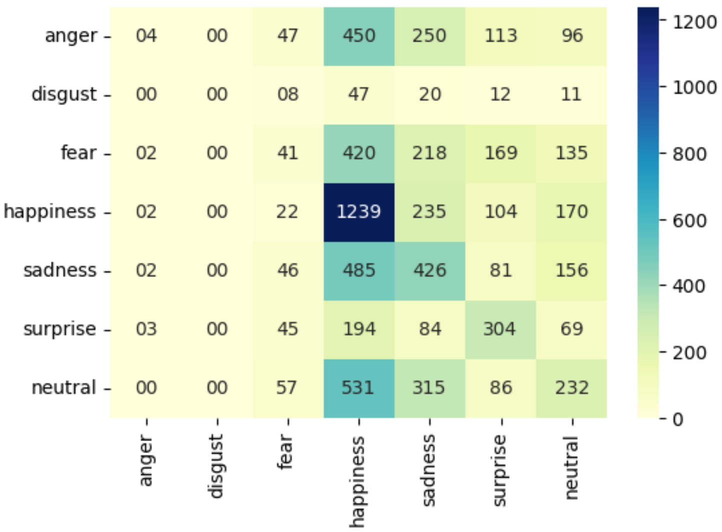

```
# Metrics
print_evaluation_metrics(y_train, train_pred, 'train')
print_evaluation_metrics(y_cv, cv_pred, 'cv')
```

```
* ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** *
train data accuracy score: 0.3216160968375486
train data weighted f1 score: 0.26444420290218945
```




```
# Test Data Performance
print_evaluation_metrics(y_test, test_pred, 'test')
print(classification_report(y_test, test_pred))
```

```
* ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** *
test data accuracy score: 0.3240513634396191
test data weighted f1 score: 0.2655519458422188
```




```
              precision    recall  f1-score   support

           0       0.31      0.00      0.01       960
           1       0.00      0.00      0.00        98
           2       0.15      0.04      0.07       985
           3       0.37      0.70      0.48      1772
           4       0.28      0.36      0.31      1196
           5       0.35      0.43      0.39       699
           6       0.27      0.19      0.22      1221

    accuracy                           0.32      6931
   macro avg       0.25      0.25      0.21      6931
weighted avg       0.29      0.32      0.27      6931
```

4. Transfer Learning using Pretrained CNN Model

Train Test Split

```
# Train Test Split (80-20 split)
X_train, X_test, y_train, y_test = train_test_split(img_data, labels, test_size=0.1, stratify=labels, random_state=4:

# Train CV Split (80-10 split)
#X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.1, stratify=y_train, random_state=42)

# Shapes
print(f'X_train shape: {X_train.shape}')
#print(f'X_cv shape:    {X_cv.shape}')
print(f'X_test shape:  {X_test.shape}')
print(f'y_train shape: {y_train.shape}')
#print(f'y_cv shape:    {y_cv.shape}')
print(f'y_test shape:  {y_test.shape}')
```

```
X_train shape: (31187, 48, 48, 3)
X_test shape:  (3466, 48, 48, 3)
```

```
y_train shape: (31187,)
y_test shape:  (3466,)
```

Encode class labels

```
# Encode class labels
ohe = OneHotEncoder()
ohe.fit(np.array(y_train).reshape(-1, 1))

y_train_enc = ohe.transform(np.array(y_train).reshape(-1,1)).todense()
#y_cv_enc = ohe.transform(np.array(y_cv).reshape(-1,1)).todense()
y_test_enc = ohe.transform(np.array(y_test).reshape(-1,1)).todense()

# Shapes
print(f'y_train_enc shape: {y_train_enc.shape}')
#print(f'y_cv_enc shape: {y_cv_enc.shape}')
print(f'y_test_enc shape: {y_test_enc.shape}')
```

```
y_train_enc shape: (31187, 7)
y_test_enc shape: (3466, 7)
```

Define Transfer Learning Network using VGG19 (Imagenet Weights)

```
# Download pretrained VGG19 Model
vgg19 = tf.keras.applications.VGG19(weights = 'imagenet',
                                    include_top = False,
                                    input_shape = (48, 48, 3))
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg19/vgg19_weights_tf_dim_ordering_tf_kernels_n
80134624/80134624 [==============================] - 5s 0us/step
```

```
# Prevent VGG layers training
for layer in vgg19.layers:
    layer.trainable = False
```

```
# VGG19 Architecture
vgg19.summary()
```

```
Model: "vgg19"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 48, 48, 3)]       0

 block1_conv1 (Conv2D)       (None, 48, 48, 64)        1792

 block1_conv2 (Conv2D)       (None, 48, 48, 64)        36928

 block1_pool (MaxPooling2D)  (None, 24, 24, 64)        0

 block2_conv1 (Conv2D)       (None, 24, 24, 128)       73856

 block2_conv2 (Conv2D)       (None, 24, 24, 128)       147584

 block2_pool (MaxPooling2D)  (None, 12, 12, 128)       0

 block3_conv1 (Conv2D)       (None, 12, 12, 256)       295168

 block3_conv2 (Conv2D)       (None, 12, 12, 256)       590080

 block3_conv3 (Conv2D)       (None, 12, 12, 256)       590080

 block3_conv4 (Conv2D)       (None, 12, 12, 256)       590080

 block3_pool (MaxPooling2D)  (None, 6, 6, 256)         0

 block4_conv1 (Conv2D)       (None, 6, 6, 512)         1180160

 block4_conv2 (Conv2D)       (None, 6, 6, 512)         2359808

 block4_conv3 (Conv2D)       (None, 6, 6, 512)         2359808

 block4_conv4 (Conv2D)       (None, 6, 6, 512)         2359808

 block4_pool (MaxPooling2D)  (None, 3, 3, 512)         0

 block5_conv1 (Conv2D)       (None, 3, 3, 512)         2359808
```

```
 block5_conv2 (Conv2D)       (None, 3, 3, 512)         2359808

 block5_conv3 (Conv2D)       (None, 3, 3, 512)         2359808

 block5_conv4 (Conv2D)       (None, 3, 3, 512)         2359808

 block5_pool (MaxPooling2D)  (None, 1, 1, 512)         0

=================================================================
Total params: 20024384 (76.39 MB)
Trainable params: 0 (0.00 Byte)
Non-trainable params: 20024384 (76.39 MB)
_________________________________________________________________
```

```
# Define Classification Layer on top
vgg_output = vgg19.layers[-2].output
op = AveragePooling2D()(vgg_output)
op = Flatten()(op)
op = Dense(512, activation='relu')(op)
op = Dense(384, activation='relu')(op)
op = Dense(96, activation='relu')(op)
op = Dense(32, activation='relu')(op)
output = Dense(7, activation = 'softmax', name = 'output_layer')(op)
```

```
# Create Model
vgg_model = tf.keras.Model(inputs=vgg19.input, outputs=output)
```

```
# Model summary
vgg_model.summary()
```

```
 block1_conv2 (Conv2D)       (None, 48, 48, 64)        36928

 block1_pool (MaxPooling2D)  (None, 24, 24, 64)        0

 block2_conv1 (Conv2D)       (None, 24, 24, 128)       73856

 block2_conv2 (Conv2D)       (None, 24, 24, 128)       147584

 block2_pool (MaxPooling2D)  (None, 12, 12, 128)       0

 block3_conv1 (Conv2D)       (None, 12, 12, 256)       295168

 block3_conv2 (Conv2D)       (None, 12, 12, 256)       590080

 block3_conv3 (Conv2D)       (None, 12, 12, 256)       590080

 block3_conv4 (Conv2D)       (None, 12, 12, 256)       590080

 block3_pool (MaxPooling2D)  (None, 6, 6, 256)         0

 block4_conv1 (Conv2D)       (None, 6, 6, 512)         1180160

 block4_conv2 (Conv2D)       (None, 6, 6, 512)         2359808

 block4_conv3 (Conv2D)       (None, 6, 6, 512)         2359808

 block4_conv4 (Conv2D)       (None, 6, 6, 512)         2359808

 block4_pool (MaxPooling2D)  (None, 3, 3, 512)         0

 block5_conv1 (Conv2D)       (None, 3, 3, 512)         2359808

 block5_conv2 (Conv2D)       (None, 3, 3, 512)         2359808

 block5_conv3 (Conv2D)       (None, 3, 3, 512)         2359808

 block5_conv4 (Conv2D)       (None, 3, 3, 512)         2359808

 average_pooling2d (Average  (None, 1, 1, 512)         0
 Pooling2D)

 flatten (Flatten)           (None, 512)               0

 dense (Dense)               (None, 512)               262656

 dense_1 (Dense)             (None, 384)               196992
```

```
Trainable params: 499943 (1.91 MB)
Non-trainable params: 20024384 (76.39 MB)
_________________________________________________________________
```

Data Augmentation

```
# Define Data Generator
image_datagen = ImageDataGenerator(rescale=1./255,
                                   rotation_range = 15,
                                   width_shift_range = 0.15,
                                   height_shift_range = 0.15,
                                   shear_range = 0.15,
                                   zoom_range = 0.15,
                                   horizontal_flip = True,)
image_datagen.fit(X_train)
```

Callbacks

```
# Create necessary directories
os.makedirs('vgg_cnn/models', exist_ok=True)
os.makedirs('vgg_cnn/logs', exist_ok=True)
```

```
# Callbacks
saver = ModelCheckpoint('/content/vgg_cnn/models/model_{epoch:02d}.hdf5', monitor='val_accuracy', verbose=1, save_be
stopper = EarlyStopping(monitor='val_accuracy', patience=11, min_delta = 0.00005, restore_best_weights=True, verbose=
reducer = ReduceLROnPlateau(monitor='val_accuracy', factor=0.5, patience=7, min_lr = 1e-7, verbose=1)
tb = TensorBoard(log_dir='/content/vgg_cnn/logs', histogram_freq=1)

callbacks = [saver, stopper, reducer, tb]
```

Model Training

```
# Params
optimizer = tf.keras.optimizers.Adam()
loss = 'categorical_crossentropy'
metrics = ['accuracy']
batch_size = 32
epochs = 100
```

```
# Compile Model
vgg_model.compile(optimizer=optimizer, loss=loss, metrics=metrics)
```

```
# Train Model
vgg_history = vgg_model.fit(image_datagen.flow(X_train, y_train_enc, batch_size = batch_size ),
                                       validation_data = image_datagen.flow(X_test, y_test_enc, batch_size = batch_s
                                       steps_per_epoch = len(X_train) / batch_size ,
                                       epochs = epochs,
                                       callbacks = callbacks)
```

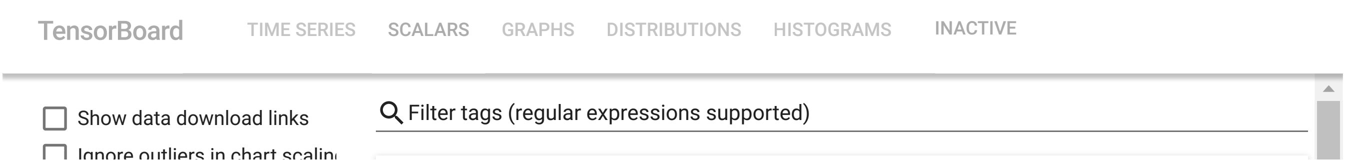
```
Epoch 43: val_accuracy did not improve from 0.38979
974/974 [==============================] - 33s 34ms/step - loss: 1.4805 - accuracy: 0.4186 - val_loss: 1.5918 - val_accuracy: 0.
Epoch 44/100
974/974 [============================>.] - ETA: 0s - loss: 1.4825 - accuracy: 0.4154
Epoch 44: val_accuracy did not improve from 0.38979
974/974 [==============================] - 33s 34ms/step - loss: 1.4827 - accuracy: 0.4153 - val_loss: 1.5956 - val_accuracy: 0.
Epoch 45/100
975/974 [==============================] - ETA: 0s - loss: 1.4839 - accuracy: 0.4189
Epoch 45: val_accuracy did not improve from 0.38979

Epoch 45: ReduceLROnPlateau reducing learning rate to 0.0002500000118743628.
974/974 [==============================] - 33s 34ms/step - loss: 1.4839 - accuracy: 0.4189 - val_loss: 1.6001 - val_accuracy: 0.
Epoch 46/100
974/974 [============================>.] - ETA: 0s - loss: 1.4631 - accuracy: 0.4300
Epoch 46: val_accuracy did not improve from 0.38979
974/974 [==============================] - 33s 34ms/step - loss: 1.4629 - accuracy: 0.4301 - val_loss: 1.5906 - val_accuracy: 0.
Epoch 47/100
974/974 [============================>.] - ETA: 0s - loss: 1.4602 - accuracy: 0.4264
Epoch 47: val_accuracy did not improve from 0.38979
974/974 [==============================] - 33s 34ms/step - loss: 1.4600 - accuracy: 0.4265 - val_loss: 1.6015 - val_accuracy: 0.
Epoch 48/100
975/974 [==============================] - ETA: 0s - loss: 1.4576 - accuracy: 0.4302
Epoch 48: val_accuracy did not improve from 0.38979
974/974 [==============================] - 33s 34ms/step - loss: 1.4576 - accuracy: 0.4302 - val_loss: 1.5985 - val_accuracy: 0.
Epoch 49/100
974/974 [============================>.] - ETA: 0s - loss: 1.4564 - accuracy: 0.4276
Epoch 49: val_accuracy did not improve from 0.38979
Restoring model weights from the end of the best epoch: 38.
974/974 [==============================] - 33s 34ms/step - loss: 1.4567 - accuracy: 0.4275 - val_loss: 1.6150 - val_accuracy: 0.
Epoch 49: early stopping
```

Model Performace Metrics

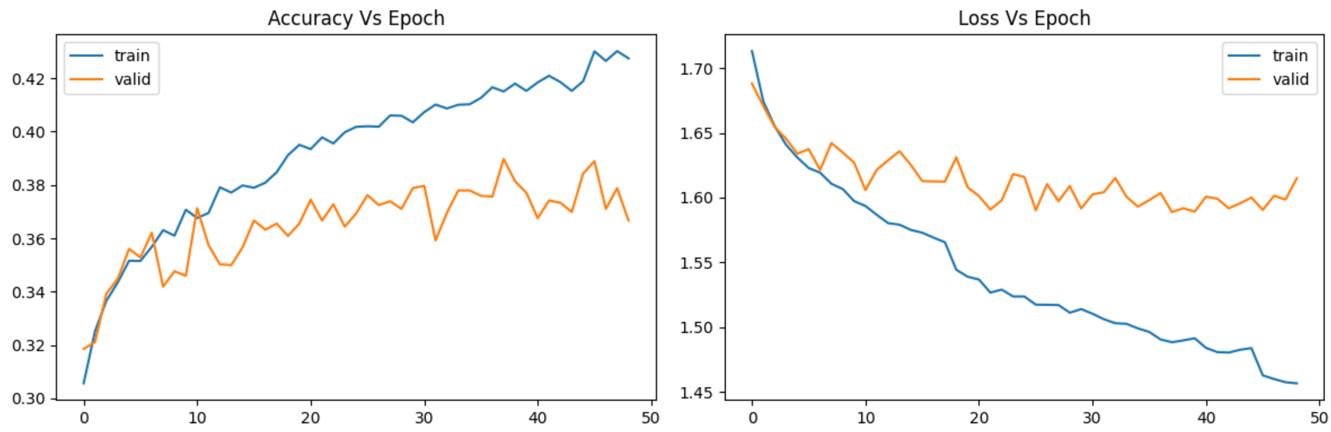
```
# Predictions
train_pred = np.argmax(vgg_model.predict(X_train*1./255), axis=1)
#cv_pred = np.argmax(vgg_model.predict(X_cv*1./255), axis=1)
test_pred = np.argmax(vgg_model.predict(X_test*1./255), axis=1)
```

```
975/975 [==============================] - 14s 14ms/step
109/109 [==============================] - 2s 14ms/step
```

```
# Tensorboard
%load_ext tensorboard
%tensorboard --logdir /content/vgg_cnn/logs
```

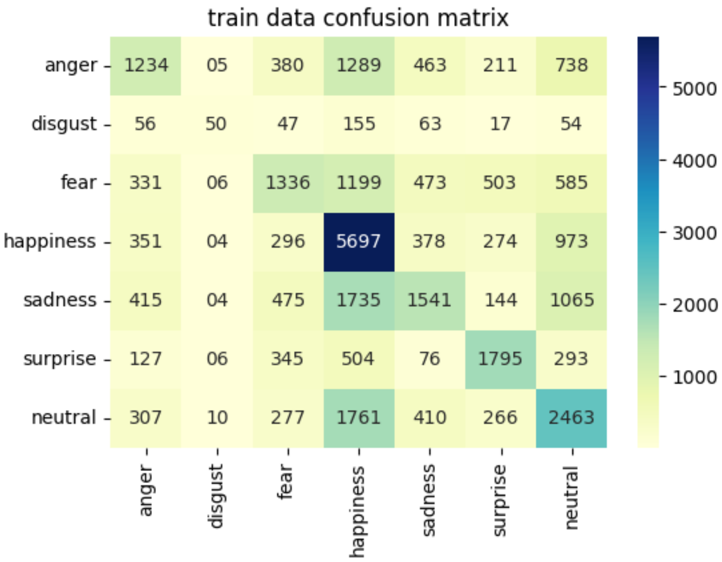



```
1 # Training Metrics
2 plot_metrics(vgg_history)
```



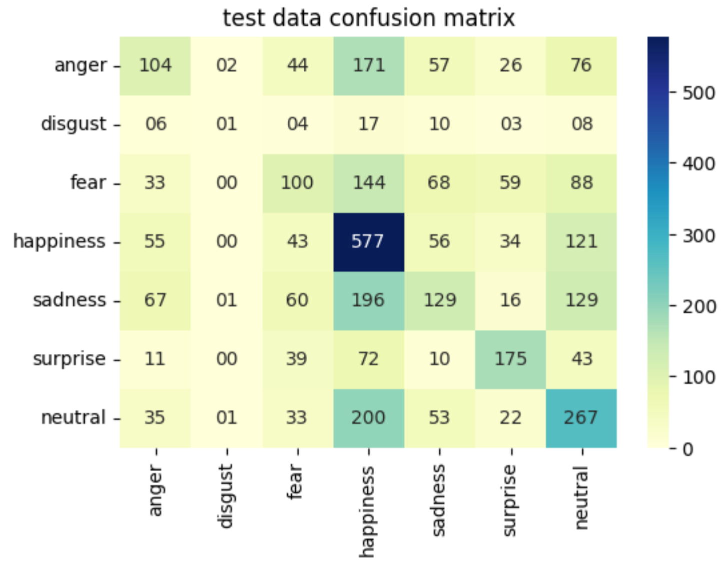

```
1 # Metrics
2 print_evaluation_metrics(y_train, train_pred, 'train')
3 #print_evaluation_metrics(y_cv, cv_pred, 'cv')
```

```
* ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** *
train data accuracy score: 0.4526244909738032
train data weighted f1 score: 0.435900908131837
```




```
1 # Test Data Performance
2 print_evaluation_metrics(y_test, test_pred, 'test')
3 print(classification_report(y_test, test_pred))
```

```
* ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** *
test data accuracy score: 0.39036353144835545
test data weighted f1 score: 0.3691946138861337
```




```
precision    recall  f1-score   support
```

5. Training VGG19 from scratch

```
2       0.31      0.29      0.25       402
```

Train Test Split

```
5       0.52      0.50      0.51       350
```

```
# Train Test Split (80-20 split)
X_train, X_test, y_train, y_test = train_test_split(img_data, labels, test_size=0.1, stratify=labels, random_state=4

# Train CV Split (80-10 split)
#X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.1, stratify=y_train, random_state=42)

# Shapes
print(f'X_train shape: {X_train.shape}')
#print(f'X_cv shape:    {X_cv.shape}')
print(f'X_test shape:  {X_test.shape}')
print(f'y_train shape: {y_train.shape}')
#print(f'y_cv shape:    {y_cv.shape}')
print(f'y_test shape:  {y_test.shape}')
```

```
X_train shape: (31187, 48, 48, 3)
X_test shape:  (3466, 48, 48, 3)
y_train shape: (31187,)
y_test shape:  (3466,)
```

Encode class labels

```
# Encode class labels
ohe = OneHotEncoder()
ohe.fit(np.array(y_train).reshape(-1, 1))

y_train_enc = ohe.transform(np.array(y_train).reshape(-1,1)).todense()
#y_cv_enc = ohe.transform(np.array(y_cv).reshape(-1,1)).todense()
y_test_enc = ohe.transform(np.array(y_test).reshape(-1,1)).todense()

# Shapes
print(f'y_train_enc shape: {y_train_enc.shape}')
#print(f'y_cv_enc shape: {y_cv_enc.shape}')
print(f'y_test_enc shape: {y_test_enc.shape}')
```

```
y_train_enc shape: (31187, 7)
y_test_enc shape: (3466, 7)
```

Define Transfer Learning Network using VGG19 (Imagenet Weights)

```
# Download pretrained VGG19 Model
vgg19 = tf.keras.applications.VGG19(weights = 'imagenet',
                                    include_top = False,
                                    input_shape = (48, 48, 3))
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg19/vgg19_weights_tf_dim_ordering_tf_kernels_n
80134624/80134624 [==============================] - 3s 0us/step
```

```
# Prevent VGG layers training
# for layer in vgg19.layers:
#     layer.trainable = False
```

```
# VGG19 Architecture
vgg19.summary()
```

```
Model: "vgg19"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 48, 48, 3)]       0

 block1_conv1 (Conv2D)       (None, 48, 48, 64)        1792

 block1_conv2 (Conv2D)       (None, 48, 48, 64)        36928

 block1_pool (MaxPooling2D)  (None, 24, 24, 64)        0

 block2_conv1 (Conv2D)       (None, 24, 24, 128)       73856

 block2_conv2 (Conv2D)       (None, 24, 24, 128)       147584

 block2_pool (MaxPooling2D)  (None, 12, 12, 128)       0

 block3_conv1 (Conv2D)       (None, 12, 12, 256)       295168

 block3_conv2 (Conv2D)       (None, 12, 12, 256)       590080

 block3_conv3 (Conv2D)       (None, 12, 12, 256)       590080

 block3_conv4 (Conv2D)       (None, 12, 12, 256)       590080

 block3_pool (MaxPooling2D)  (None, 6, 6, 256)         0

 block4_conv1 (Conv2D)       (None, 6, 6, 512)         1180160

 block4_conv2 (Conv2D)       (None, 6, 6, 512)         2359808

 block4_conv3 (Conv2D)       (None, 6, 6, 512)         2359808

 block4_conv4 (Conv2D)       (None, 6, 6, 512)         2359808

 block4_pool (MaxPooling2D)  (None, 3, 3, 512)         0

 block5_conv1 (Conv2D)       (None, 3, 3, 512)         2359808

 block5_conv2 (Conv2D)       (None, 3, 3, 512)         2359808

 block5_conv3 (Conv2D)       (None, 3, 3, 512)         2359808

 block5_conv4 (Conv2D)       (None, 3, 3, 512)         2359808

 block5_pool (MaxPooling2D)  (None, 1, 1, 512)         0

=================================================================
Total params: 20024384 (76.39 MB)
Trainable params: 20024384 (76.39 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

```
# Define Classification Layer on top
vgg_output = vgg19.layers[-2].output
op = GlobalAveragePooling2D()(vgg_output)
output = Dense(7, activation = 'softmax', name = 'output_layer')(op)
```

```
# Create Model
full_vgg_model = tf.keras.Model(inputs=vgg19.input, outputs=output)
```

```
# Model summary
full_vgg_model.summary()
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 48, 48, 3)]       0
```

```
 block1_conv1 (Conv2D)       (None, 48, 48, 64)        1792

 block1_conv2 (Conv2D)       (None, 48, 48, 64)        36928

 block1_pool (MaxPooling2D)  (None, 24, 24, 64)        0

 block2_conv1 (Conv2D)       (None, 24, 24, 128)       73856

 block2_conv2 (Conv2D)       (None, 24, 24, 128)       147584

 block2_pool (MaxPooling2D)  (None, 12, 12, 128)       0

 block3_conv1 (Conv2D)       (None, 12, 12, 256)       295168

 block3_conv2 (Conv2D)       (None, 12, 12, 256)       590080

 block3_conv3 (Conv2D)       (None, 12, 12, 256)       590080

 block3_conv4 (Conv2D)       (None, 12, 12, 256)       590080

 block3_pool (MaxPooling2D)  (None, 6, 6, 256)         0

 block4_conv1 (Conv2D)       (None, 6, 6, 512)         1180160

 block4_conv2 (Conv2D)       (None, 6, 6, 512)         2359808

 block4_conv3 (Conv2D)       (None, 6, 6, 512)         2359808

 block4_conv4 (Conv2D)       (None, 6, 6, 512)         2359808

 block4_pool (MaxPooling2D)  (None, 3, 3, 512)         0

 block5_conv1 (Conv2D)       (None, 3, 3, 512)         2359808

 block5_conv2 (Conv2D)       (None, 3, 3, 512)         2359808

 block5_conv3 (Conv2D)       (None, 3, 3, 512)         2359808

 block5_conv4 (Conv2D)       (None, 3, 3, 512)         2359808

 global_average_pooling2d (  (None, 512)               0
 GlobalAveragePooling2D)

 output_layer (Dense)        (None, 7)                 3591

=================================================================
Total params: 20027975 (76.40 MB)
Trainable params: 20027975 (76.40 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Data Augmentation

```
# Define Data Generator
image_datagen = ImageDataGenerator(rescale=1./255,
                                   rotation_range = 15,
                                   width_shift_range = 0.15,
                                   height_shift_range = 0.15,
                                   shear_range = 0.15,
                                   zoom_range = 0.15,
                                   horizontal_flip = True,)
image_datagen.fit(X_train)
```

Callbacks

```
# Create necessary directories
os.makedirs('full_vgg_cnn/models/', exist_ok=True)
os.makedirs('full_vgg_cnn/logs/', exist_ok=True)
```

```
# Callbacks
saver = ModelCheckpoint('/content/full_vgg_cnn/models/model_{epoch:02d}.hdf5', monitor='val_accuracy', verbose=1, sa
stopper = EarlyStopping(monitor='val_accuracy', patience=11, min_delta = 0.00005, restore_best_weights=True, verbose
reducer = ReduceLROnPlateau(monitor='val_accuracy', factor=0.5, patience=7, min_lr = 1e-7, verbose=1)
tb = TensorBoard(log_dir='/content/full_vgg_cnn/logs', histogram_freq=1)

callbacks = [saver, stopper, reducer, tb]
```

Model Training

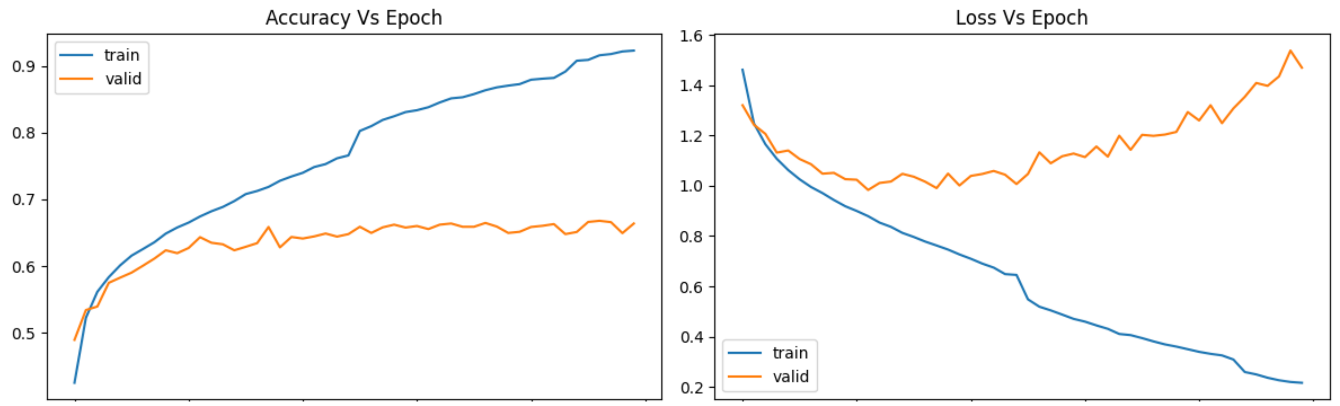
```
# Params
optimizer = tf.keras.optimizers.Adam(learning_rate = 0.0001, beta_1 = 0.9, beta_2 = 0.999)
loss = 'categorical_crossentropy'
metrics = ['accuracy']
batch_size = 32
epochs = 50
```

```
# Compile Model
full_vgg_model.compile(optimizer=optimizer, loss=loss, metrics=metrics)
```

```
# Train Model
full_vgg_history = full_vgg_model.fit(image_datagen.flow(X_train, y_train_enc, batch_size = batch_size ),
                                      validation_data = image_datagen.flow(X_test, y_test_enc, batch_size = batch_s
                                      steps_per_epoch = len(X_train) / batch_size ,
                                      epochs = epochs,
                                      callbacks = callbacks)
```

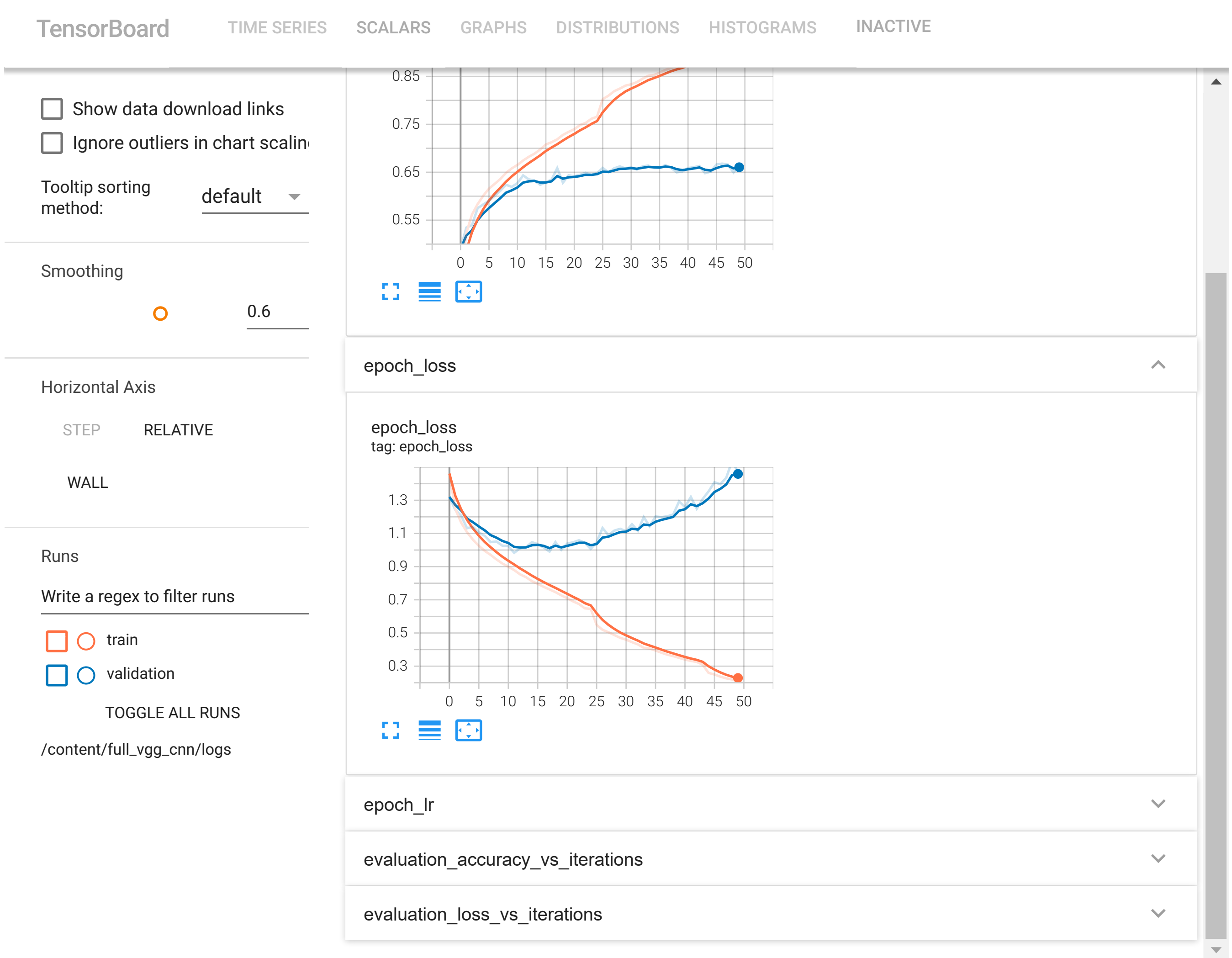
```
975/974 [==============================] - ETA: 0s - loss: 0.3811 - accuracy: 0.8634
Epoch 37: val_accuracy improved from 0.66388 to 0.66474, saving model to /content/full_vgg_cnn/models/model_37.hdf5
974/974 [==============================] - 51s 52ms/step - loss: 0.3811 - accuracy: 0.8634 - val_loss: 1.1983 - val_accuracy: 0.
Epoch 38/50
974/974 [============================>.] - ETA: 0s - loss: 0.3692 - accuracy: 0.8677
Epoch 38: val_accuracy did not improve from 0.66474
974/974 [==============================] - 51s 52ms/step - loss: 0.3693 - accuracy: 0.8677 - val_loss: 1.2033 - val_accuracy: 0.
Epoch 39/50
974/974 [============================>.] - ETA: 0s - loss: 0.3602 - accuracy: 0.8704
Epoch 39: val_accuracy did not improve from 0.66474
974/974 [==============================] - 51s 52ms/step - loss: 0.3605 - accuracy: 0.8703 - val_loss: 1.2139 - val_accuracy: 0.
Epoch 40/50
975/974 [==============================] - ETA: 0s - loss: 0.3501 - accuracy: 0.8726
Epoch 40: val_accuracy did not improve from 0.66474
974/974 [==============================] - 51s 52ms/step - loss: 0.3501 - accuracy: 0.8726 - val_loss: 1.2930 - val_accuracy: 0.
Epoch 41/50
974/974 [============================>.] - ETA: 0s - loss: 0.3399 - accuracy: 0.8791
Epoch 41: val_accuracy did not improve from 0.66474
974/974 [==============================] - 51s 52ms/step - loss: 0.3396 - accuracy: 0.8791 - val_loss: 1.2594 - val_accuracy: 0.
Epoch 42/50
975/974 [==============================] - ETA: 0s - loss: 0.3317 - accuracy: 0.8807
Epoch 42: val_accuracy did not improve from 0.66474
974/974 [==============================] - 51s 52ms/step - loss: 0.3317 - accuracy: 0.8807 - val_loss: 1.3201 - val_accuracy: 0.
Epoch 43/50
974/974 [============================>.] - ETA: 0s - loss: 0.3255 - accuracy: 0.8818
Epoch 43: val_accuracy did not improve from 0.66474
974/974 [==============================] - 51s 52ms/step - loss: 0.3255 - accuracy: 0.8819 - val_loss: 1.2487 - val_accuracy: 0.
Epoch 44/50
974/974 [============================>.] - ETA: 0s - loss: 0.3093 - accuracy: 0.8912
Epoch 44: val_accuracy did not improve from 0.66474

Epoch 44: ReduceLROnPlateau reducing learning rate to 2.499999936844688e-05.
974/974 [==============================] - 51s 52ms/step - loss: 0.3091 - accuracy: 0.8913 - val_loss: 1.3073 - val_accuracy: 0.
Epoch 45/50
975/974 [==============================] - ETA: 0s - loss: 0.2594 - accuracy: 0.9076
Epoch 45: val_accuracy did not improve from 0.66474
974/974 [==============================] - 51s 52ms/step - loss: 0.2594 - accuracy: 0.9076 - val_loss: 1.3534 - val_accuracy: 0.
Epoch 46/50
975/974 [==============================] - ETA: 0s - loss: 0.2498 - accuracy: 0.9089
Epoch 46: val_accuracy improved from 0.66474 to 0.66619, saving model to /content/full_vgg_cnn/models/model_46.hdf5
974/974 [==============================] - 51s 52ms/step - loss: 0.2498 - accuracy: 0.9089 - val_loss: 1.4085 - val_accuracy: 0.
Epoch 47/50
974/974 [============================>.] - ETA: 0s - loss: 0.2365 - accuracy: 0.9158
Epoch 47: val_accuracy improved from 0.66619 to 0.66792, saving model to /content/full_vgg_cnn/models/model_47.hdf5
974/974 [==============================] - 51s 53ms/step - loss: 0.2366 - accuracy: 0.9157 - val_loss: 1.3972 - val_accuracy: 0.
Epoch 48/50
975/974 [==============================] - ETA: 0s - loss: 0.2266 - accuracy: 0.9176
Epoch 48: val_accuracy did not improve from 0.66792
974/974 [==============================] - 51s 52ms/step - loss: 0.2266 - accuracy: 0.9176 - val_loss: 1.4349 - val_accuracy: 0.
Epoch 49/50
974/974 [============================>.] - ETA: 0s - loss: 0.2200 - accuracy: 0.9214
Epoch 49: val_accuracy did not improve from 0.66792
974/974 [==============================] - 51s 52ms/step - loss: 0.2198 - accuracy: 0.9215 - val_loss: 1.5373 - val_accuracy: 0.
Epoch 50/50
974/974 [============================>.] - ETA: 0s - loss: 0.2164 - accuracy: 0.9228
Epoch 50: val_accuracy did not improve from 0.66792
974/974 [==============================] - 51s 52ms/step - loss: 0.2165 - accuracy: 0.9228 - val_loss: 1.4694 - val_accuracy: 0.
```

```
# Training Metrics
plot_metrics(full_vgg_history)
```



Model Performace Metrics

```
# Tensorboard
%load_ext tensorboard
%tensorboard --logdir /content/full_vgg_cnn/logs
```




```
# Load Epoch 18 (Best Model)
best_vgg = tf.keras.models.load_model('/content/full_vgg_cnn/models/model_18.hdf5')
```

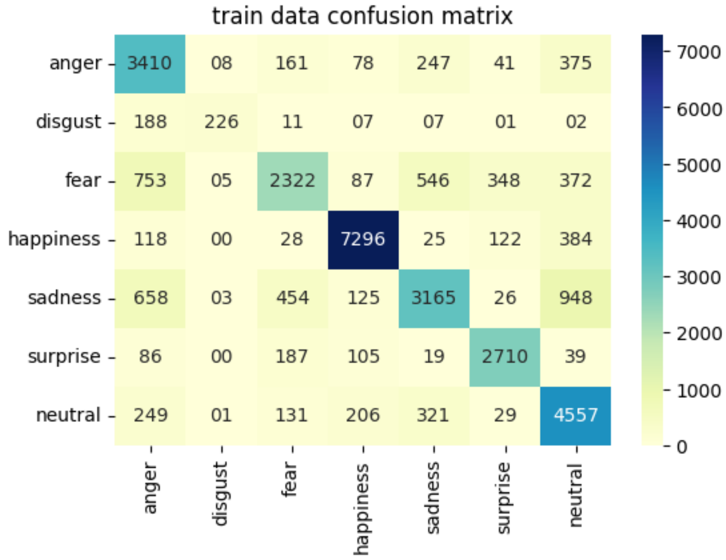
```
# Predictions
train_pred = np.argmax(best_vgg.predict(X_train*1./255), axis=1)
#cv_pred = np.argmax(vgg_model.predict(X_cv*1./255), axis=1)
test_pred = np.argmax(best_vgg.predict(X_test*1./255), axis=1)
```

```
975/975 [==============================] - 13s 13ms/step
109/109 [==============================] - 1s 13ms/step
```

```
# Metrics
print evaluation metrics(v train. train pred. 'train')
```

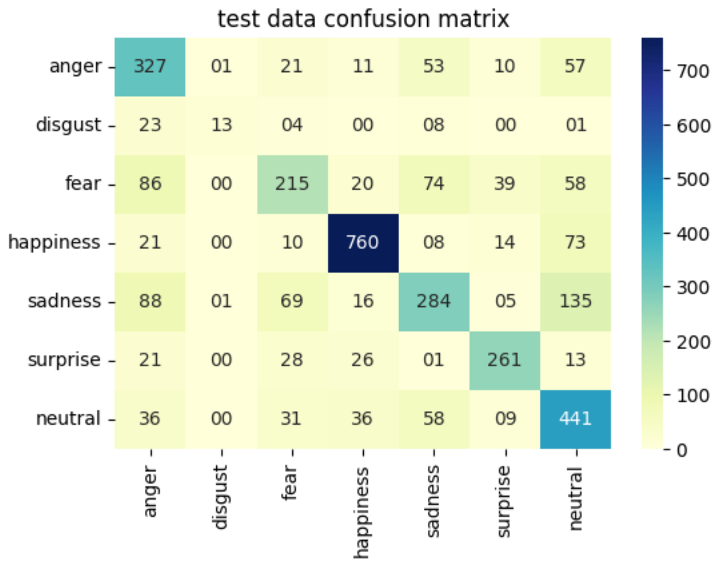
```
2 print_evaluation_metrics(y_train, train_pred, 'train')
3 #print_evaluation_metrics(y_cv, cv_pred, 'cv')
```

```
* ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** *
train data accuracy score: 0.7594831179658191
train data weighted f1 score: 0.755805075671032
```




```
1 # Test Data Performance
2 print_evaluation_metrics(y_test, test_pred, 'test')
3 print(classification_report(y_test, test_pred))
```

```
* ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** *
test data accuracy score: 0.6638776687824581
test data weighted f1 score: 0.6599664679499141
```




```
              precision    recall  f1-score   support

           0       0.54      0.68      0.60       480
           1       0.87      0.27      0.41        49
           2       0.57      0.44      0.49       492
           3       0.87      0.86      0.87       886
           4       0.58      0.47      0.52       598
           5       0.77      0.75      0.76       350
           6       0.57      0.72      0.63       611

    accuracy                           0.66      3466
   macro avg       0.68      0.60      0.61      3466
weighted avg       0.67      0.66      0.66      3466
```

Model Experiments Summary

```
1 from prettytable import PrettyTable
2
3 # Specify the Column Names while initializing the Table
4 summary = PrettyTable(["Model Info", "Test Accuracy", "Test Weighted F1 "])
```

```

# Add rows
summary.add_row(["SVM Classifier", "0.43", "0.40"])
summary.add_row(["MLP Model", "0.33", "0.26"])
summary.add_row(["Custom CNN", "0.32", "0.27"])
summary.add_row(["Transfer Learning (VGG19)", "0.39", "0.37"])
summary.add_row(["Fully Trained VGG19", "0.66", "0.66"])

print("Model Experiments Summary: ")
print(summary)
```

```
Model Experiments Summary:
+---------------------------+--------------+------------------+
|         Model Info        | Test Accuracy | Test Weighted F1 |
+---------------------------+--------------+------------------+
|       SVM Classifier      |     0.43     |       0.40       |
|         MLP Model         |     0.33     |       0.26       |
|         Custom CNN        |     0.32     |       0.27       |
| Transfer Learning (VGG19) |     0.39     |       0.37       |
|    Fully Trained VGG19    |     0.66     |       0.66       |
+---------------------------+--------------+------------------+
```

AS we can observe in the summary table, fully trained VGG19 from scratch showed best performance on test data. This model can be fine-tuned further to improve performance.

Fine Tuning Best Model

With my experimentation till now, we could find best model as VGG19.

It can further be experimented with different batch_sizes, epochs, learning_rates, optimizers and augmentation parameters.

Best Model Performance Analysis

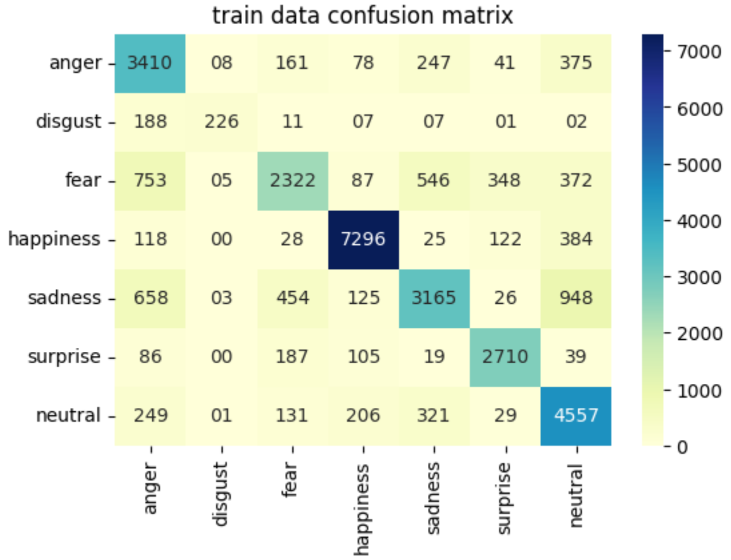
```
# Load Epoch 18 (Best Model)
best_vgg = tf.keras.models.load_model('/content/full_vgg_cnn/models/model_18.hdf5')
```

```
# Predictions
train_pred = np.argmax(best_vgg.predict(X_train*1./255), axis=1)
#cv_pred = np.argmax(vgg_model.predict(X_cv*1./255), axis=1)
test_pred = np.argmax(best_vgg.predict(X_test*1./255), axis=1)
```

```
975/975 [==============================] - 13s 13ms/step
109/109 [==============================] - 1s 13ms/step
```

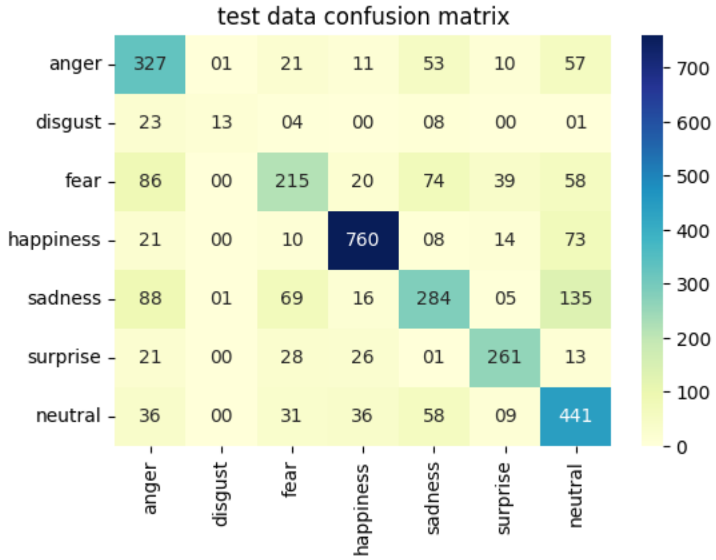
```
# Metrics
print_evaluation_metrics(y_train, train_pred, 'train')
#print_evaluation_metrics(y_cv, cv_pred, 'cv')
```

```
* ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** *
train data accuracy score: 0.7594831179658191
train data weighted f1 score: 0.755805075671032
```



```
1 # Test Data Performance
2 print_evaluation_metrics(y_test, test_pred, 'test')
3 print(classification_report(y_test, test_pred))
```

```
* ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** ** *
test data accuracy score: 0.6638776687824581
test data weighted f1 score: 0.6599664679499141
```




```
              precision    recall  f1-score   support

           0       0.54      0.68      0.60       480
           1       0.87      0.27      0.41        49
           2       0.57      0.44      0.49       492
           3       0.87      0.86      0.87       886
           4       0.58      0.47      0.52       598
           5       0.77      0.75      0.76       350
           6       0.57      0.72      0.63       611

    accuracy                           0.66      3466
   macro avg       0.68      0.60      0.61      3466
weighted avg       0.67      0.66      0.66      3466
```

BEST MODEL REMARKS:

1. Our model is best able to detect happiness with 87% f1 score.
2. It can also detect surprise, neutral with moderate performance at 76%, 63% and 60% f1 score respectively.
3. Model is confused between sadness-neutral, anger-sadness, anger-fear.

Adding more data and/or further tuning/experimenting can improve model performance.

Future Scope

1. Different state of the art CNN Models like VGGFace, InceptionV3, ResNet, EfficientNet etc. can be experimented.
2. Transfer learning techniques can be used with more prominent dense layers and enabling tarining for bottom 10-15% layers.
3. Different more deeper architectures can be tried for MLP and Custom CNN networks .
4. Other ML algorithms with different hyperparameters can be experimented with for MultiClass Classification.
5. Some emotions like sadness and neutral look similar for some people, combining these to labels could improve overall model performance.

Bonus Task

The Emotion Detection from Webcam feed is Implemented at following Github repo link.

Link: https://github.com/theingale/face_emotion_detection