Modeling-LR-XGB-LGBM-TREE

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1 Author Information

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Github: https://github.com/miladshiraniUCB/Emotion-Detection-in-Speech.git

2 Introduction

In this notebook, we will try to train some categorical models namely, logistic regression, decision tree, random forest, xgboost and LightGBM. In order to train these models, we will covert the audio files into numerical values and will feed these numerical values into the above mentioned models to train them. According the the results we will see, we can conclude that this approach may not yield a good model for our purposes.

3 Importing Libraries

In this section, we will import the libraries that we are going to use in this notebook.

[2]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import os
import librosa
import librosa.display
from tqdm import tqdm

import tensorflow as tf
import tensorflow_io as tfio
import noisereduce as nr
```

```python
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import confusion_matrix, plot_confusion_matrix,␣
 ↪classification_report
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.decomposition import PCA

import lightgbm as lgb
import xgboost as xgb
from imblearn.over_sampling import SMOTE, ADASYN

import warnings
warnings.filterwarnings('ignore')
```

```
/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/xgboost/compat.py:93:
FutureWarning: pandas.Int64Index is deprecated and will be removed from pandas
in a future version. Use pandas.Index with the appropriate dtype instead.
  from pandas import MultiIndex, Int64Index
```

4 Functions

The functions that we are going to use in this notebook are presented here. These functions are:

print_results: this function print the classification report for both train and test sets also it will plot the confusion matrix.

get_wave: This function will load an audio file and convert it to a vector values data.

zero_padding: This function is modified version of the function introduced in here and it creates an uniform size arrays to be used for the ML models.

4.1 Printing results of models

[80]:
```python
def print_results(model, X_train=X_train, y_train=y_train
                  ,X_test=X_test, y_test=y_test):

    fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(15,10))

    ax1 = axes[0]
    plot_confusion_matrix(model, X_test, y_test,
                          display_labels=le.classes_,
                          cmap=plt.cm.Blues, ax = ax1)

    ax1.set_title("Confusion Matrix for Test Set")

    ax2 = axes[1]
```

```
    plot_confusion_matrix(model, X_train, y_train,
                          display_labels=le.classes_,
                          cmap=plt.cm.Blues, ax = ax2)


    ax2.set_title("Confusion Matrix for Train Set")



    ### Presenting Classification Report as a DataFrame

    train_class = classification_report(y_train, model.predict(X_train),␣
↪output_dict = True)
    test_class  = classification_report(y_test, model.predict(X_test),␣
↪output_dict = True)

    train_df = pd.DataFrame(train_class)
    test_df  = pd.DataFrame(test_class)

    train_df["data"] = "TRAIN"
    test_df["data"] = "TEST"


    report = pd.concat([test_df, train_df], axis = 0)
    report.rename(columns = {"6": f"{list(le.inverse_transform([1]))[0]}",
                             "5": f"{list(le.inverse_transform([1]))[0]}",
                             "4": f"{list(le.inverse_transform([1]))[0]}",
                             "3": f"{list(le.inverse_transform([1]))[0]}",
                             "2": f"{list(le.inverse_transform([1]))[0]}",
                             "1": f"{list(le.inverse_transform([1]))[0]}",
                             "0": f"{list(le.inverse_transform([0]))[0]}"},␣
↪inplace = True)
    report["index"] = list(report.index)

    report.set_index(["data", "index"], inplace = True)

    for item in list(report.columns):
        report[item] = report[item].apply(lambda x: np.round(x,2))


    return report
```

4.2 Converting audio files to numerical values

[13]:
```
def get_wave(filename):
    wav, sample_rate = librosa.load(filename)
    wav_reduced = nr.reduce_noise(y=wav, sr=sample_rate)
#     wav = tf.squeeze(wav, axis=-1)
#     sample_rate = tf.cast(sample_rate, dtype=tf.int64)
#     wav = tfio.audio.resample(wav, rate_in=sample_rate, rate_out=16000)
    return wav_reduced
```

4.3 Creating equal size arrays for training

[14]:
```
def zero_padding(filename, n_slice = 60000):

    waveform = get_wave(filename)
    waveform = waveform[:n_slice]
    zero_padding = tf.zeros([n_slice] - tf.shape(waveform),
      dtype =tf.float32)

    waveform = tf.cast(waveform, dtype = tf.float32)
    equal_length = tf.concat([waveform, zero_padding], axis = 0)

    return equal_length
```

5 Importing Data

In this section, we will import the train and test sets and in the next section we will create numerical values to train the models.

[8]:
```
train = pd.read_csv("../Train-Test-Split/train.csv")
test = pd.read_csv("../Train-Test-Split/test.csv")

train.drop("Unnamed: 0", axis = 1, inplace = True)
test.drop("Unnamed: 0", axis = 1, inplace = True)
```

[9]:
```
train.head()
```

[9]:
```
                                                path                 name  \
0  /Users/miladshirani/Documents/Flatiron/phase_5…    YAF_neat_angry.wav
1  /Users/miladshirani/Documents/Flatiron/phase_5…       YAF_life_ps.wav
2  /Users/miladshirani/Documents/Flatiron/phase_5…  OAF_love_neutral.wav
3  /Users/miladshirani/Documents/Flatiron/phase_5…   YAF_peg_neutral.wav
4  /Users/miladshirani/Documents/Flatiron/phase_5…   OAF_young_angry.wav

     target
0     angry
1  surprise
```

```
2    neutral
3    neutral
4      angry
```

6 Converting Audio to Vectors

In this section, we will convert the audio files to numerical arrays of equal size to train models with. First we try to create a numerical dataframe for `train` set.

First we will create a dataframe called `X_train` whose index is the index of the `train` set. Also each column will represent a numerical value of the intensity of the audio file in the specific time. Therefore, the columns are time steps and the value in that column is the intensity of the audio file that we showed graphically in the previous notebook. Each row of this dataframe is numerical values of each audio file that are transformed by the function `zero_padding`. Since this function gives an array, we are going to convert that array to a dataframe and then we will save the transposed of the created dataframe in `X_train` dataframe. We do the similar procedure for the `test` set and make `X_test` dataframe from the `test` set.

[15]:
```
n_slice = 60000

X_train = pd.DataFrame(columns = list(range(0, n_slice)),
                       index = train.index)
print("train_wave ZERO  DONE!")

for i in range(0,len(train)):
    path   = train["path"].iloc[i]
    values = zero_padding(path)
    X_train.iloc[i] = pd.DataFrame(values).transpose()
print("train is DONE")
```

```
train_wave ZERO  DONE!
train is DONE
```

In the following we will show the slice of the created X_train dataframe

[20]:
```
X_train_slice = X_train.iloc[:, 40:55].copy()
X_train_slice.head()
```

[20]:
```
         40        41        42        43        44        45        46  \
0 -0.000112 -0.000126  0.000005 -0.000056 -0.000126 -0.000094 -0.000044
1  0.000026 -0.000006 -0.000005  0.000041 -0.000026  0.000025  0.000019
2 -0.000034 -0.000035 -0.000036 -0.000036 -0.000037 -0.000038 -0.000039
3 -0.000021 -0.000024 -0.000029 -0.000018  0.000001 -0.000026 -0.000039
4 -0.000027 -0.000028 -0.000028 -0.000029  -0.00003 -0.000031 -0.000032

         47        48        49        50        51        52        53  \
0 -0.000011 -0.000144 -0.000109  0.000005 -0.000078  -0.00011 -0.000057
1 -0.000006  0.000028  0.000008  0.000011  0.000027  0.000015  0.000001
```

```
2  -0.00004 -0.000041 -0.000042 -0.000043 -0.000044 -0.000045 -0.000046
3 -0.000014 -0.000007 -0.000026  -0.00003 -0.000016 -0.000017 -0.000039
4 -0.000032 -0.000033 -0.000034 -0.000035 -0.000036 -0.000037 -0.000037

         54
0 -0.000079
1  0.000048
2 -0.000047
3 -0.000012
4 -0.000038
```

In the next, we will create a `X_test` by using the same procedure we introduced to create the `X_train` dataset.

[18]:
```
n_slice = 60000

X_test = pd.DataFrame(columns = list(range(0, n_slice)),
                         index = test.index)
print("test_wave ZERO  DONE!")

for i in range(0,len(test)):
    path   = train["path"].iloc[i]
    values = zero_padding(path)
    X_test.iloc[i] = pd.DataFrame(values).transpose()
print("test is DONE")
```

```
test_wave ZERO  DONE!
test is DONE
```

[19]:
```
X_test_slice = X_test.iloc[:, 40:55].copy()
X_test_slice.head()
```

[19]:
```
         40        41        42        43        44        45        46  \
0 -0.000112 -0.000126  0.000005 -0.000056 -0.000126 -0.000094 -0.000044
1  0.000026 -0.000006 -0.000005  0.000041 -0.000026  0.000025  0.000019
2 -0.000034 -0.000035 -0.000036 -0.000036 -0.000037 -0.000038 -0.000039
3 -0.000021 -0.000024 -0.000029 -0.000018  0.000001 -0.000026 -0.000039
4 -0.000027 -0.000028 -0.000028 -0.000029  -0.00003 -0.000031 -0.000032

         47        48        49        50        51        52        53  \
0 -0.000011 -0.000144 -0.000109  0.000005 -0.000078  -0.00011 -0.000057
1 -0.000006  0.000028  0.000008  0.000011  0.000027  0.000015  0.000001
2  -0.00004 -0.000041 -0.000042 -0.000043 -0.000044 -0.000045 -0.000046
3 -0.000014 -0.000007 -0.000026  -0.00003 -0.000016 -0.000017 -0.000039
4 -0.000032 -0.000033 -0.000034 -0.000035 -0.000036 -0.000037 -0.000037

         54
```

```
0 -0.000079
1  0.000048
2 -0.000047
3 -0.000012
4 -0.000038
```

Now in the next code, we will one-hot encode the categories to be used for the modeling.

[58]:
```python
le = LabelEncoder()
y_train = le.fit_transform(train["target"])
y_test  = le.transform(test["target"])
```

7 Modeling

In this section, we will train categorical models, namely logistic regression, decision tree, random forest, xgboos and lightgbm on the numerical arrays obtained by converting audio files.

7.1 Logistic Regression

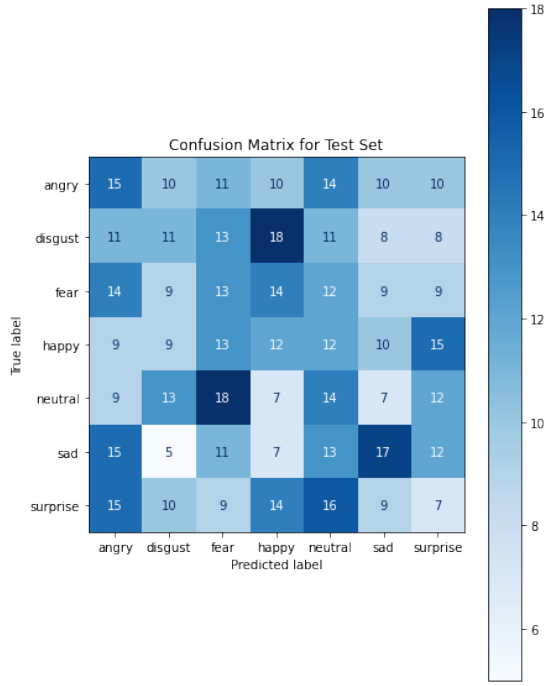
[64]:
```python
lr = LogisticRegression(solver='liblinear',random_state=42)
lr.fit(X_train, y_train)
print("Fitting Done!")
```

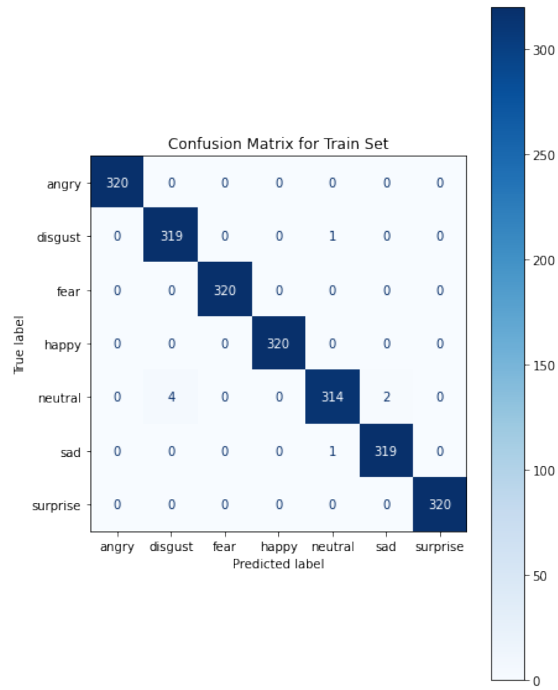
```
Fitting Done!
```

[71]:
```python
print_results(lr)
```

[71]:
```
                   angry  disgust  disgust  disgust  disgust  disgust  disgust  \
data  index
TEST  precision     0.17     0.16     0.15     0.15     0.15     0.24     0.10
      recall        0.19     0.14     0.16     0.15     0.18     0.21     0.09
      f1-score      0.18     0.15     0.15     0.15     0.16     0.23     0.09
      support      80.00    80.00    80.00    80.00    80.00    80.00    80.00
TRAIN precision     1.00     0.99     1.00     1.00     0.99     0.99     1.00
      recall        1.00     1.00     1.00     1.00     0.98     1.00     1.00
      f1-score      1.00     0.99     1.00     1.00     0.99     1.00     1.00
      support     320.00   320.00   320.00   320.00   320.00   320.00   320.00

                 accuracy  macro avg  weighted avg
data  index
TEST  precision      0.16       0.16          0.16
      recall         0.16       0.16          0.16
      f1-score       0.16       0.16          0.16
      support        0.16     560.00        560.00
TRAIN precision      1.00       1.00          1.00
      recall         1.00       1.00          1.00
      f1-score       1.00       1.00          1.00
```

```
support          1.00     2240.00        2240.00
```





7.2 Decision Tree

[72]:

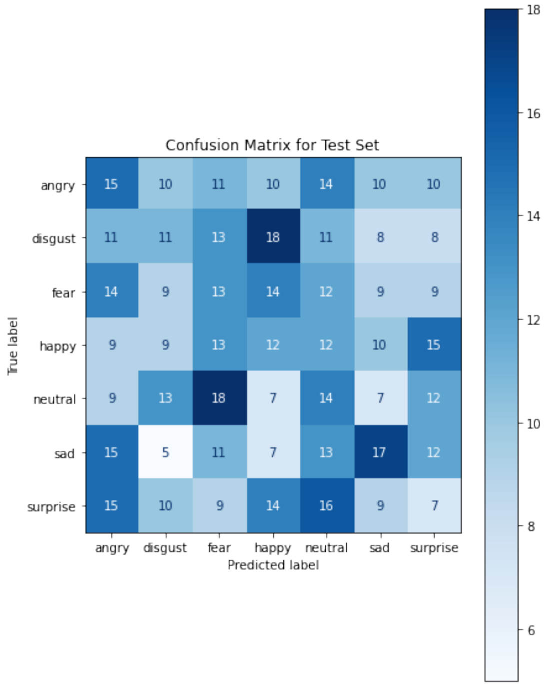
```python
tree = DecisionTreeClassifier()
tree.fit(X_train, y_train)

print("Fitting Tree")
print_results(tree)
```

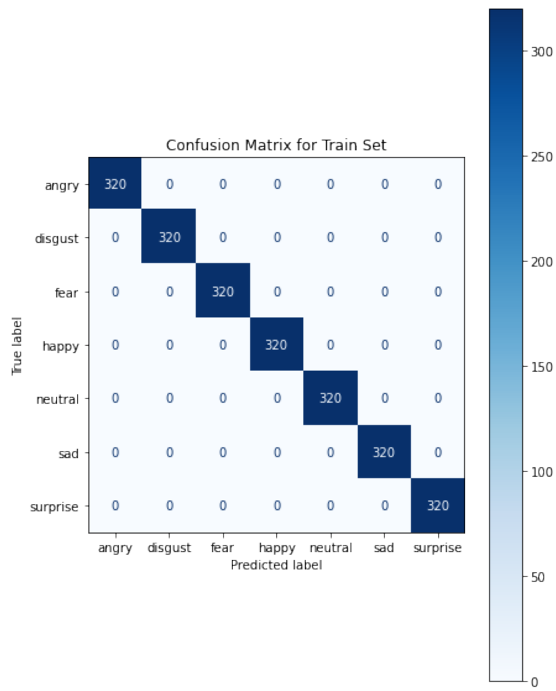
```
Fitting Tree
```

[72]:

```
                        angry  disgust  disgust  disgust  disgust  disgust  disgust  \
data  index
TEST  precision          0.17     0.16     0.15     0.15     0.15     0.24     0.10
      recall             0.19     0.14     0.16     0.15     0.18     0.21     0.09
      f1-score           0.18     0.15     0.15     0.15     0.16     0.23     0.09
      support           80.00    80.00    80.00    80.00    80.00    80.00    80.00
TRAIN precision          1.00     1.00     1.00     1.00     1.00     1.00     1.00
      recall             1.00     1.00     1.00     1.00     1.00     1.00     1.00
      f1-score           1.00     1.00     1.00     1.00     1.00     1.00     1.00
      support          320.00   320.00   320.00   320.00   320.00   320.00   320.00

                      accuracy  macro avg  weighted avg
```

```
data  index
TEST  precision      0.16       0.16          0.16
      recall         0.16       0.16          0.16
      f1-score       0.16       0.16          0.16
      support        0.16     560.00        560.00
TRAIN precision      1.00       1.00          1.00
      recall         1.00       1.00          1.00
      f1-score       1.00       1.00          1.00
      support        1.00    2240.00       2240.00
```





7.3 Random Forest

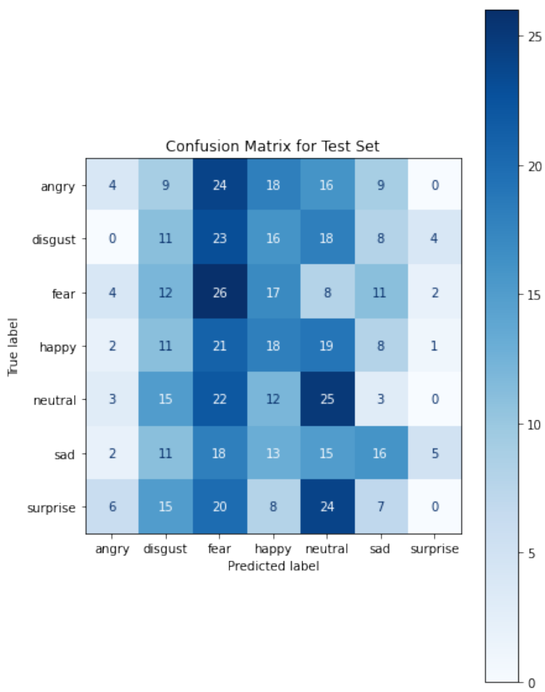
[74]:
```
forest = RandomForestClassifier(criterion="entropy",
                                n_estimators= 20,
                                max_depth = 5,
                                bootstrap = True,
                                random_state = 42)

forest.fit(X_train, y_train)

print("Fitting Tree")
print_results(forest)
```

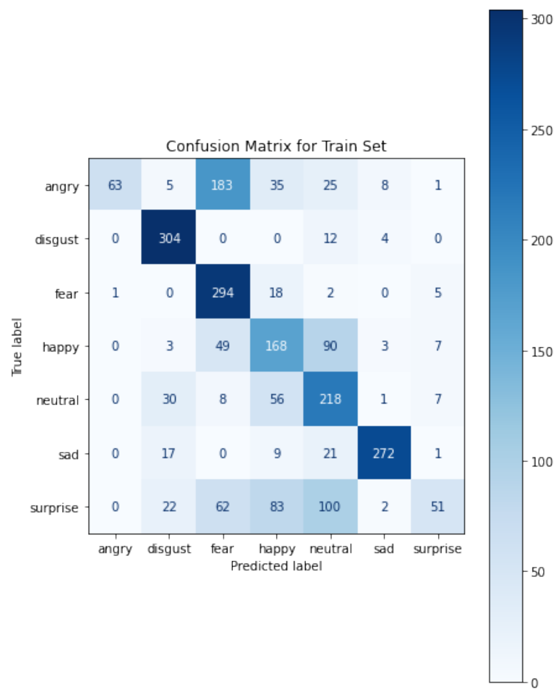
```
Fitting Tree
```

[74]:

data	index	angry	disgust	disgust	disgust	disgust	disgust	disgust
TEST	precision	0.19	0.13	0.17	0.18	0.20	0.26	0.00
	recall	0.05	0.14	0.32	0.22	0.31	0.20	0.00
	f1-score	0.08	0.13	0.22	0.20	0.24	0.23	0.00
	support	80.00	80.00	80.00	80.00	80.00	80.00	80.00
TRAIN	precision	0.98	0.80	0.49	0.46	0.47	0.94	0.71
	recall	0.20	0.95	0.92	0.52	0.68	0.85	0.16
	f1-score	0.33	0.87	0.64	0.49	0.55	0.89	0.26
	support	320.00	320.00	320.00	320.00	320.00	320.00	320.00

data	index	accuracy	macro avg	weighted avg
TEST	precision	0.18	0.16	0.16
	recall	0.18	0.18	0.18
	f1-score	0.18	0.16	0.16
	support	0.18	560.00	560.00
TRAIN	precision	0.61	0.69	0.69
	recall	0.61	0.61	0.61
	f1-score	0.61	0.58	0.58
	support	0.61	2240.00	2240.00





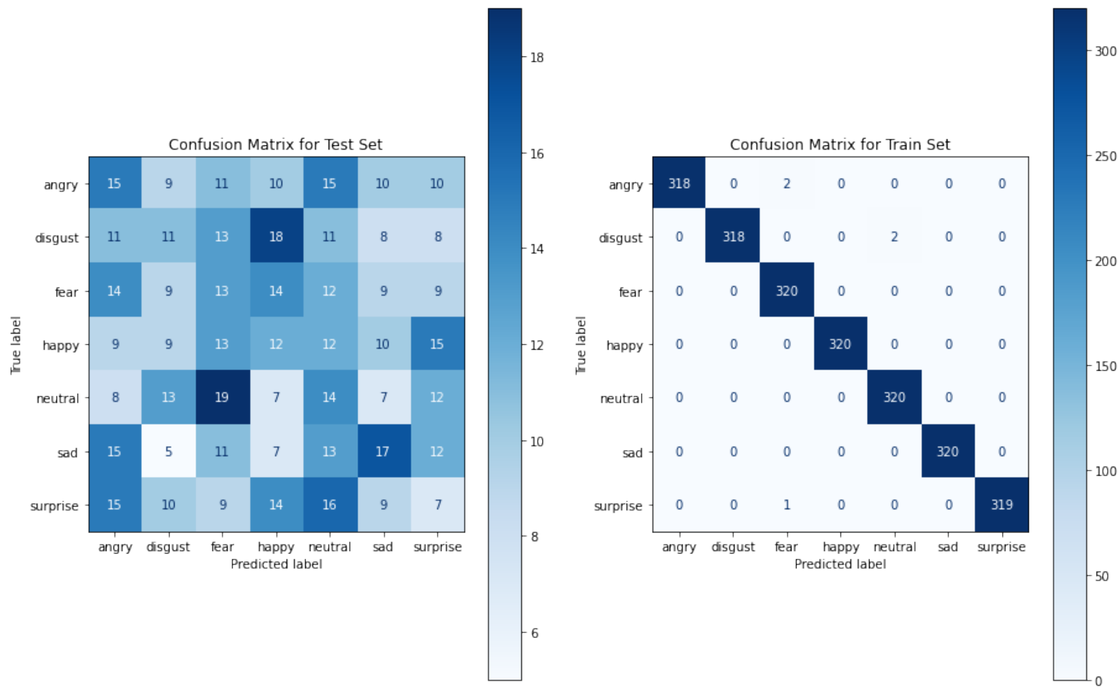
7.4 XGBoost

[81]:
```
xg = xgb.XGBClassifier(max_depth = 10, n_estimators= 15, seed=42,
                        alpha = 10,
                        objective = 'multi:softmax',
                        num_class = 7,
                        eval_metric = "auc")

xg.fit(X_train.values, y_train)

print("Fitting Done")
```

```
Fitting Done
```

[82]:
```
print_results(xg, X_train=X_train.values, y_train=y_train
                  ,X_test=X_test.values, y_test=y_test)
```

[82]:
```
                  angry  disgust  disgust  disgust  disgust  disgust  disgust  \
data  index
TEST  precision    0.17     0.17     0.15     0.15     0.15     0.24     0.10
      recall       0.19     0.14     0.16     0.15     0.18     0.21     0.09
      f1-score     0.18     0.15     0.15     0.15     0.16     0.23     0.09
      support     80.00    80.00    80.00    80.00    80.00    80.00    80.00
TRAIN precision    1.00     1.00     0.99     1.00     0.99     1.00     1.00
      recall       0.99     0.99     1.00     1.00     1.00     1.00     1.00
      f1-score     1.00     1.00     1.00     1.00     1.00     1.00     1.00
      support    320.00   320.00   320.00   320.00   320.00   320.00   320.00

                 accuracy  macro avg  weighted avg
data  index
TEST  precision      0.16       0.16          0.16
      recall         0.16       0.16          0.16
      f1-score       0.16       0.16          0.16
      support        0.16     560.00        560.00
TRAIN precision      1.00       1.00          1.00
      recall         1.00       1.00          1.00
      f1-score       1.00       1.00          1.00
      support        1.00    2240.00       2240.00
```



7.5 LightGBM

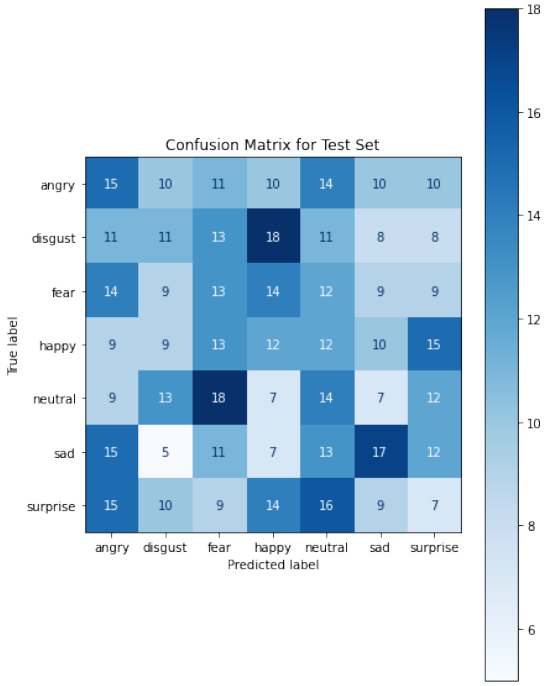
[84]:
```
params = {'num_boost_round':100,
        'learning_rate':0.02,
        'objective' : 'multiclass',
        'num_class' : 7,
        'depth':10,
        'eval_metric':'AUC',
        # 'verbose':200,
        'od_type':"Iter", # overfit detector
        'od_wait':500, # most recent best iteration to wait before stopping
        'random_seed': 42
          }


# num_boost_round=100
light = lgb.LGBMClassifier(**params)
light.fit(X_train.values, y_train)

print("Fitting Done")
```

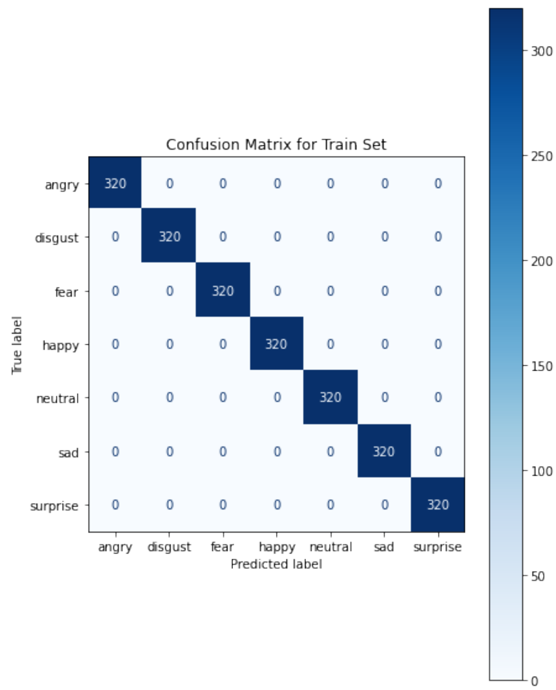
```
[LightGBM] [Warning] Unknown parameter: od_type
[LightGBM] [Warning] Unknown parameter: depth
[LightGBM] [Warning] Unknown parameter: eval_metric
[LightGBM] [Warning] Unknown parameter: od_wait
```

```
[LightGBM] [Warning] num_iterations is set=100, num_boost_round=100 will be
ignored. Current value: num_iterations=100
Fitting Done
```

[85]:
```python
print_results(light , X_train = X_train.values, y_train = y_train,
                      X_test  = X_test.values , y_test  = y_test)
```

[85]:
```
                    angry  disgust  disgust  disgust  disgust  disgust  disgust  \
data  index
TEST  precision      0.17     0.16     0.15     0.15     0.15     0.24     0.10
      recall         0.19     0.14     0.16     0.15     0.18     0.21     0.09
      f1-score       0.18     0.15     0.15     0.15     0.16     0.23     0.09
      support       80.00    80.00    80.00    80.00    80.00    80.00    80.00
TRAIN precision      1.00     1.00     1.00     1.00     1.00     1.00     1.00
      recall         1.00     1.00     1.00     1.00     1.00     1.00     1.00
      f1-score       1.00     1.00     1.00     1.00     1.00     1.00     1.00
      support      320.00   320.00   320.00   320.00   320.00   320.00   320.00

                 accuracy  macro avg  weighted avg
data  index
TEST  precision      0.16       0.16          0.16
      recall         0.16       0.16          0.16
      f1-score       0.16       0.16          0.16
      support        0.16     560.00        560.00
TRAIN precision      1.00       1.00          1.00
      recall         1.00       1.00          1.00
      f1-score       1.00       1.00          1.00
      support        1.00    2240.00       2240.00
```





8 Results and Conclusion

As we can see, these models did not perform well and we will need to try other way of modeling such as neural network. In the next notebook, we will present,design and train some neural networks on the mel spectrograms obtained in the EDA notebook.