Audio_classification

April 16, 2023

1 Music genre Classification

Dataset: The GTZAN dataset is the most-used public dataset for evaluation in machine listening research for music genre recognition (MGR). The files were collected in 2000-2001 from a variety of sources including personal CDs, radio, microphone recordings, in order to represent a variety of recording conditions (http://marsyas.info/downloads/datasets.html). The dataset include: - genres original - A collection of 10 genres with 100 audio files each, all having a length of 30 seconds (the famous GTZAN dataset, the MNIST of sounds) - images original - A visual representation for each audio file. One way to classify data is through neural networks. Because NNs (like CNN, what we will be using today) usually take in some sort of image representation, the audio files were converted to Mel Spectrograms to make this possible. - 2 CSV files - Containing features of the audio files. One file has for each song (30 seconds long) a mean and variance computed over multiple features that can be extracted from an audio file. The other file has the same structure, but the songs were split before into 3 seconds audio files (this way increasing 10 times the amount of data we fuel into our classification models). With data, more is always better.

Our project will use GTZAN dataset for music genre classifcation. The process includes the following 5 parts. 1. Visualize audio dataset: soundwave visualization, Fourier transform, Spectrogram, Mel Spectrogram, Harmonics and percussive, MFCC 2. EDA: Correlation among features & PCA 4. Classification through feature data: Gtzan dataset have extracted import features as a new dataset, such as chroma_stft_mean, chroma_stft_var, rms_mean, rms_var, spectral_centroid_mean. We can use it as a feature dataset for classification. 5. Classification through audio images: Beside classifying through features, we also process the image data from audio files and perform classification. In the end, we compare the performance between classifying through feature data and audio images.

1.1 1. Visualize Audio Data

[ ]:
```
# Usual Libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import sklearn

# Librosa (the mother of audio files)
import librosa
```

```
import librosa.display
import IPython.display as ipd
```

[ ]:
```
import os
path = 'GTZAN/'
print(list(os.listdir(f'{path}/genres_original/')))
```

```
['pop', 'metal', 'disco', 'blues', 'reggae', 'classical', 'rock', 'hiphop',
'country', 'jazz']
```

[ ]:
```
# Importing 1 file
y_pop, sr_pop = librosa.load(f'{path}/genres_original/pop/pop.00036.wav')

print('y:', y_pop, '\n')
print('y shape:', np.shape(y_pop), '\n')
print('Sample Rate (KHz):', sr_pop, '\n')

# Verify length of the audio
print('Check Len of Audio:', 661504/22050)
```

```
y: [-0.19229126 -0.08969116  0.02322388 … -0.16653442 -0.0585022
  0.01345825]

y shape: (661504,)

Sample Rate (KHz): 22050

Check Len of Audio: 30.00018140589569
```

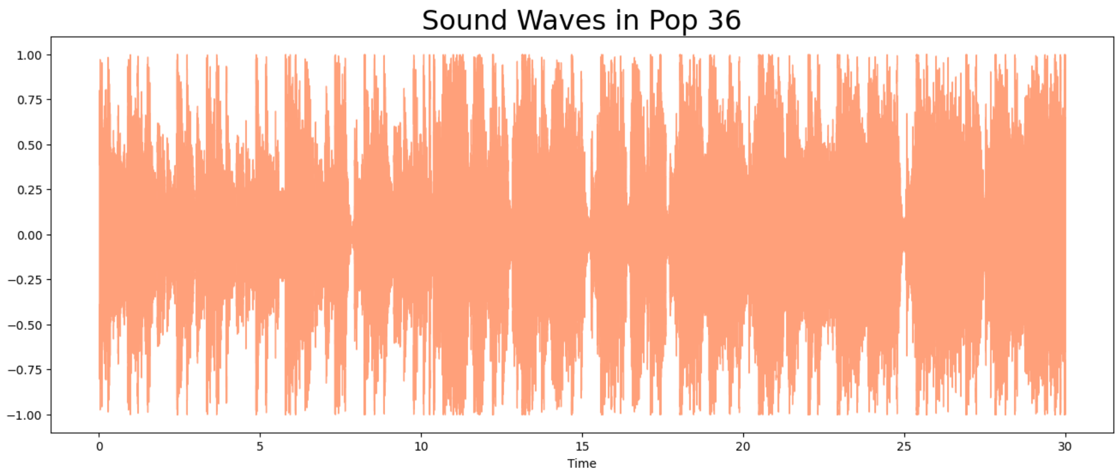
The sample rate of 22050 Hz was commonly used in early digital audio formats, such as the Audio Compact Disc (CD), which was introduced in the 1980s. CD audio is sampled at a rate of 44.1 kHz, which is twice the sample rate of 22050 Hz.

The reason why 44.1 kHz was chosen as the standard for CD audio is because it is capable of accurately representing audio frequencies up to 20 kHz, which is the upper limit of human hearing.

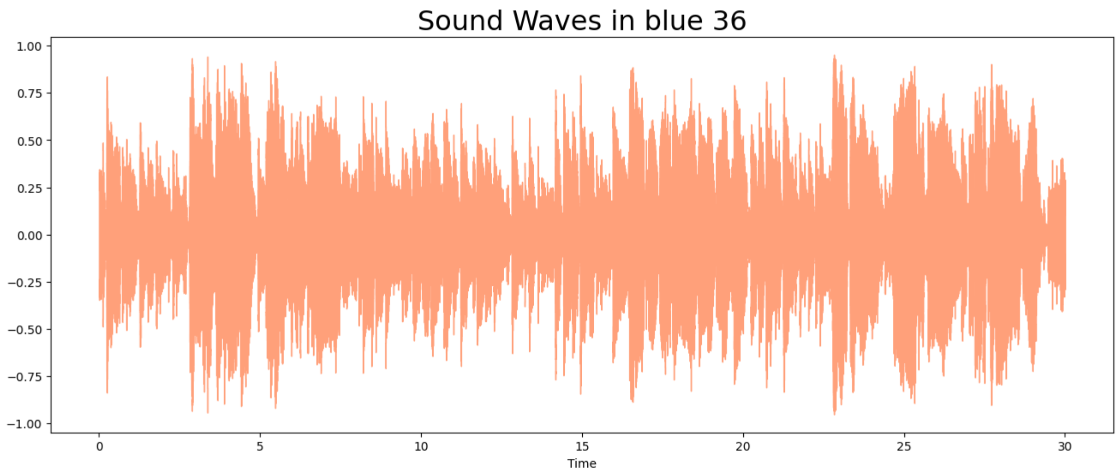
1.1.1 2D Representation: Sound Waves

Note on waveshow: x-axis represents time and the y-axis represents the amplitude of the audio signal.

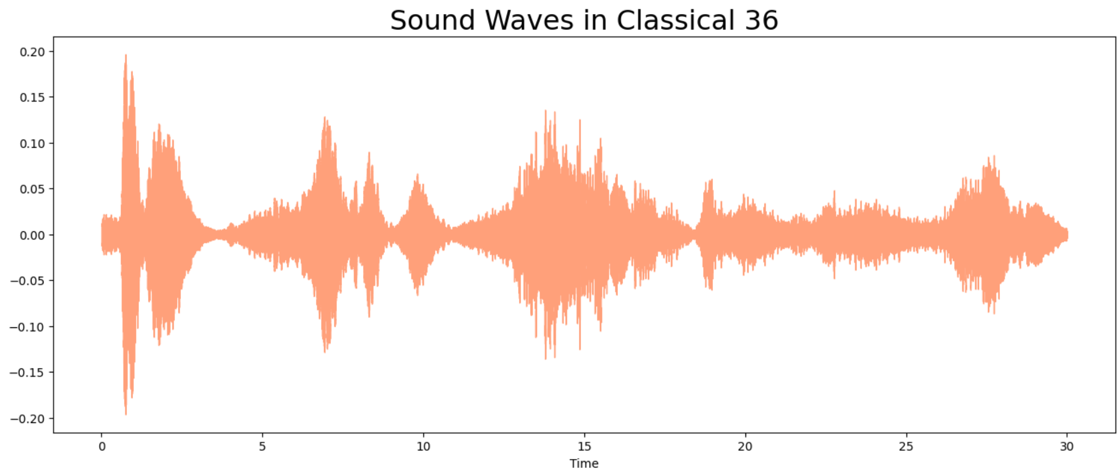
[ ]:
```
plt.figure(figsize = (16, 6))
librosa.display.waveshow(y=y_pop, sr=sr_pop, color='#FFA07A')
plt.title("Sound Waves in Pop 36", fontsize = 23);
```



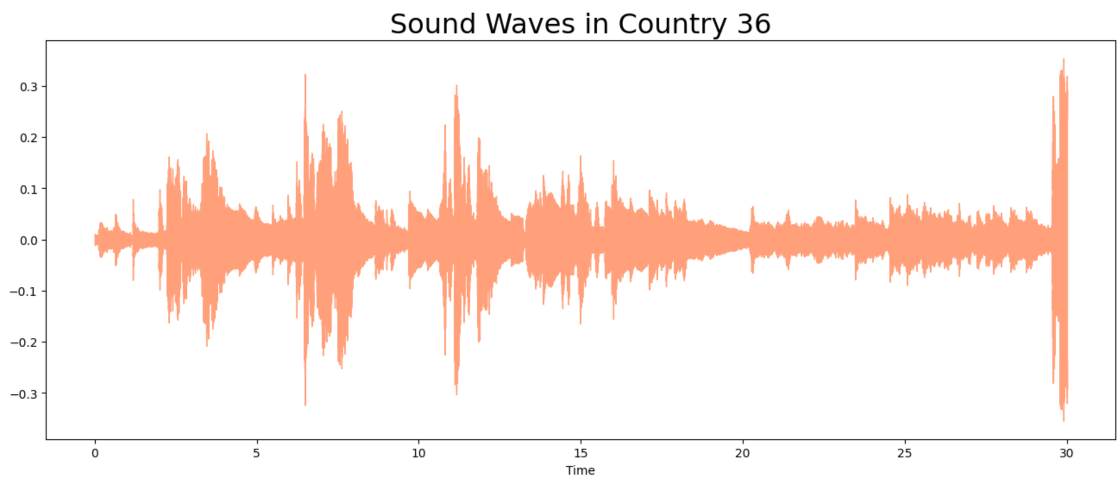

```
[ ]: y_blue, sr_blue = librosa.load(f'{path}/genres_original/blues/blues.00036.wav')

plt.figure(figsize = (16, 6))
librosa.display.waveshow(y=y_blue, sr=sr_blue, color='#FFA07A')
plt.title("Sound Waves in blue 36", fontsize = 23);
```




```
[ ]: y_classical, sr_classical = librosa.load(f'{path}/genres_original/classical/
  ↪classical.00036.wav')

plt.figure(figsize = (16, 6))
librosa.display.waveshow(y=y_classical, sr=sr_classical, color='#FFA07A')
plt.title("Sound Waves in Classical 36", fontsize = 23);
```




```
[ ]: y_country, sr_country = librosa.load(f'{path}/genres_original/country/country.
     ↪00036.wav')

     plt.figure(figsize = (16, 6))
     librosa.display.waveshow(y=y_country, sr=sr_country, color='#FFA07A')
     plt.title("Sound Waves in Country 36", fontsize = 23);
```



1.1.2 Fourier Transform

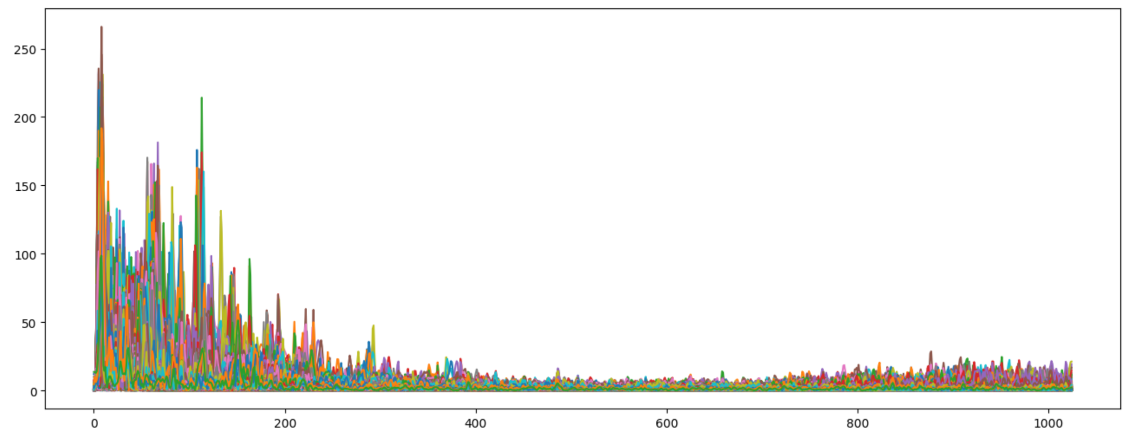
Function that gets a signal in the time domain as input, and outputs its decomposition into frequencies Transform both the y-axis (frequency) to log scale, and the "color" axis (amplitude) to Decibels, which is approx. the log scale of amplitudes.

```
[ ]: # Default FFT window size
n_fft = 2048 # FFT window size
hop_length = 512 # number audio of frames between STFT columns (looks like a␣
 ↪good default)

# Short-time Fourier transform (STFT)
D = np.abs(librosa.stft(y_pop, n_fft = n_fft, hop_length = hop_length))

print('Shape of D object:', np.shape(D))
```

```
Shape of D object: (1025, 1293)
```

The purpose of STFT is to add the time dimension back by breaking down signals into windows. (Window length: the time length of the window, hope length: the extent of window overlapping. The longer the hop length, the higher the freq resolutions (larger segments of the audio signals), but the lower the time resolution (few frames per unit of time) We then perform a Fourier transformation of the window to understand the pattern of the sounds.

```
[ ]: plt.figure(figsize = (16, 6))
plt.plot(D);
```

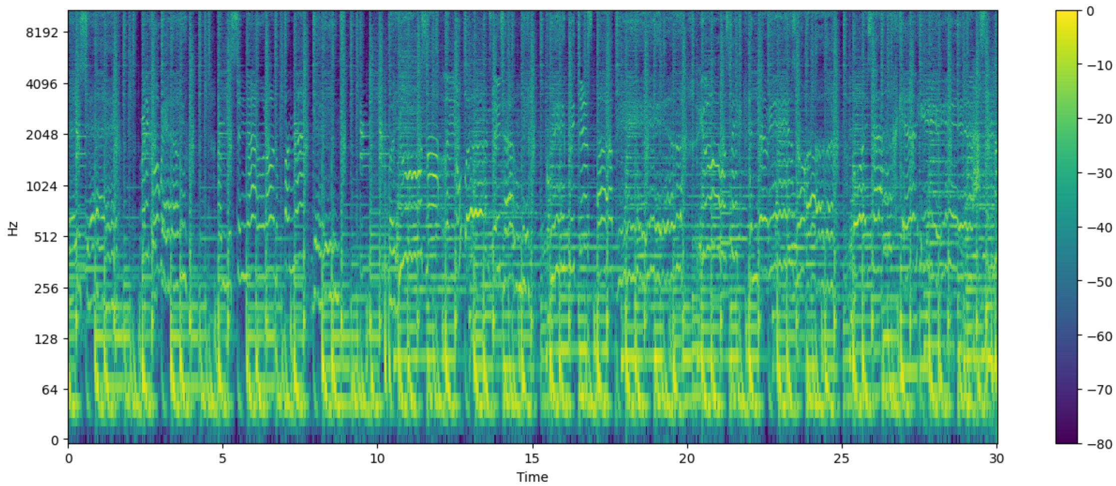


The resulting plot will show the frequency content of the audio signal over time. The x-axis of the plot represents time, with each point on the axis corresponding to a different time frame. The y-axis represents the frequency content of the signal, with each point on the axis corresponding to a different frequency band.

1.1.3 Spectrogram

The horizontal axis of a spectrogram represents time, while the vertical axis represents frequency. The intensity of the spectrogram is represented by color or grayscale, with brighter colors indicating higher intensity or amplitude at a given frequency.

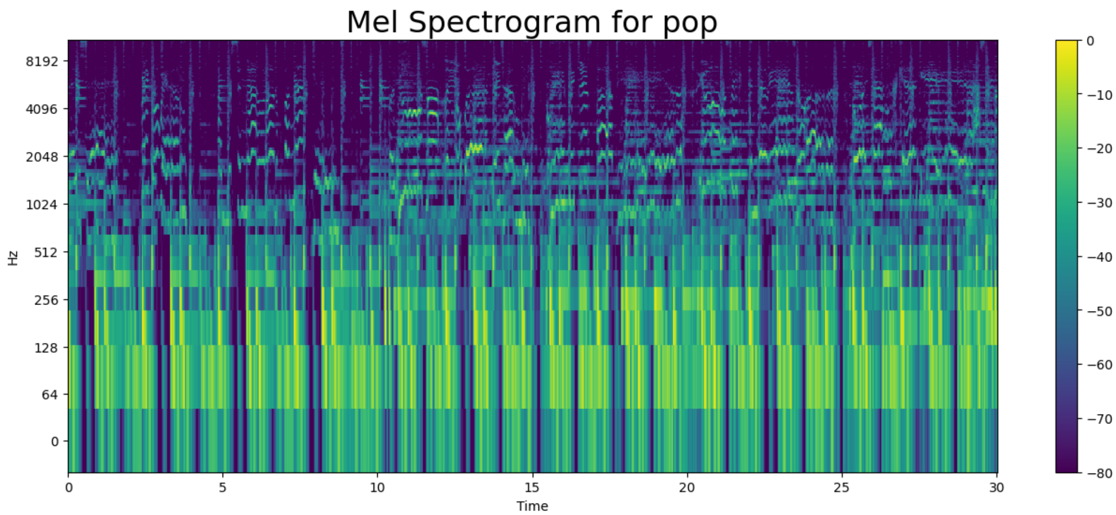
```
[ ]: # Convert an amplitude spectrogram to Decibels-scaled spectrogram.
DB = librosa.amplitude_to_db(D, ref = np.max)

# Creating the Spectogram
plt.figure(figsize = (16, 6))
librosa.display.specshow(DB, sr = sr_pop, hop_length = hop_length, x_axis =␣
 ↪'time', y_axis = 'log',
                        cmap = 'viridis')
plt.colorbar();
```



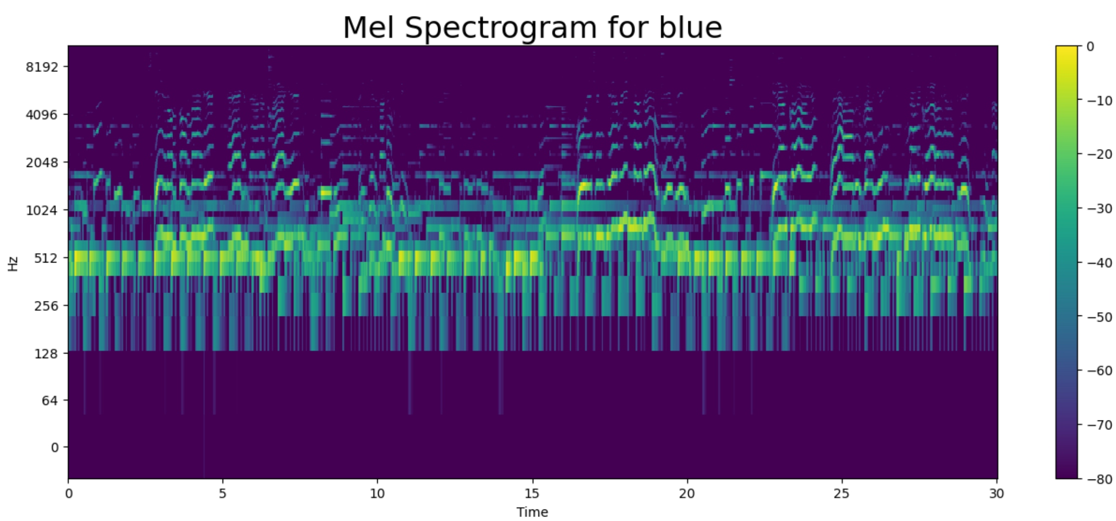
1.1.4 Mel Spectrogram

Mel Scale - frequency for humans (Reason: human perceive the sound distance unlinearly)

```
[ ]: S = librosa.feature.melspectrogram(y = y_pop, sr=sr_pop)
S_DB = librosa.amplitude_to_db(S, ref=np.max)
plt.figure(figsize = (16, 6))
librosa.display.specshow(S_DB, sr=sr_pop, hop_length=hop_length, x_axis =␣
 ↪'time', y_axis = 'log',
                        cmap = 'viridis');
plt.colorbar();
plt.title("Mel Spectrogram for pop", fontsize = 23);
```

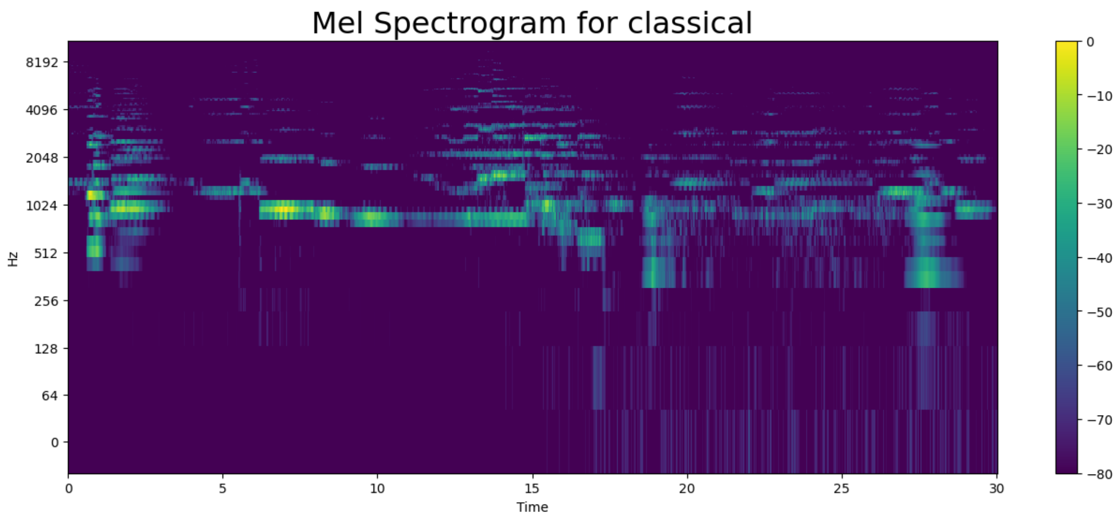


[ ]:
```
S = librosa.feature.melspectrogram(y = y_blue, sr=sr_blue)
S_DB = librosa.amplitude_to_db(S, ref=np.max)
plt.figure(figsize = (16, 6))
librosa.display.specshow(S_DB, sr=sr_blue, hop_length=hop_length, x_axis =␣
↪'time', y_axis = 'log',
                        cmap = 'viridis');
plt.colorbar();
plt.title("Mel Spectrogram for blue", fontsize = 23);
```



[ ]:
```
S = librosa.feature.melspectrogram(y = y_classical, sr=sr_classical)
S_DB = librosa.amplitude_to_db(S, ref=np.max)
```

```
plt.figure(figsize = (16, 6))
librosa.display.specshow(S_DB, sr=sr_classical, hop_length=hop_length, x_axis =
↪'time', y_axis = 'log',
                        cmap = 'viridis');
plt.colorbar();
plt.title("Mel Spectrogram for classical", fontsize = 23);
```



Observations: Pop music have higher amplitudes. Blue music have smaller range of freuqency. Classical music seems to have the most dynamic frequency.

1.1.5 Audio Features

Zero Crossing Rate: Zero Crossing Rate (ZCR) is a measure of the number of times a signal crosses the zero-axis (amplitude) in a given time frame.

[ ]:
```
# Total zero_crossings for pop
zero_crossings = librosa.zero_crossings(y_pop, pad=False)
print(sum(zero_crossings))

# Total zero_crossings for blue
zero_crossings = librosa.zero_crossings(y_blue, pad=False)
print(sum(zero_crossings))

# Total zero_crossings in our 1 song
zero_crossings = librosa.zero_crossings(y_classical, pad=False)
print(sum(zero_crossings))
```

```
76229
24463
39405
```

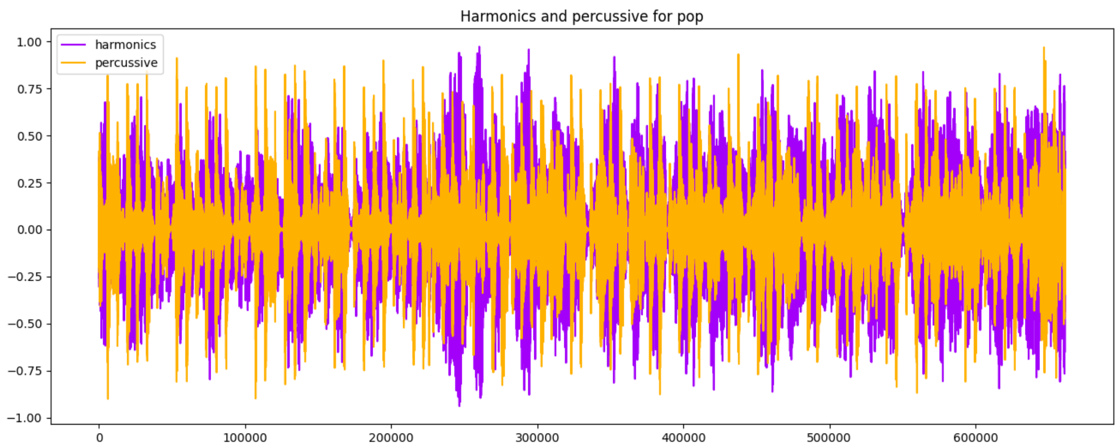
1.1.6 Harmonics and percussive

- Harmonics: These are pitch sounds that enable us to hear melodies.
- Percussive sound: This is more like something originating from an instrument onset, like a beat on a drum.

The x-axis represents time and the y-axis represents the amplitude of the signal.

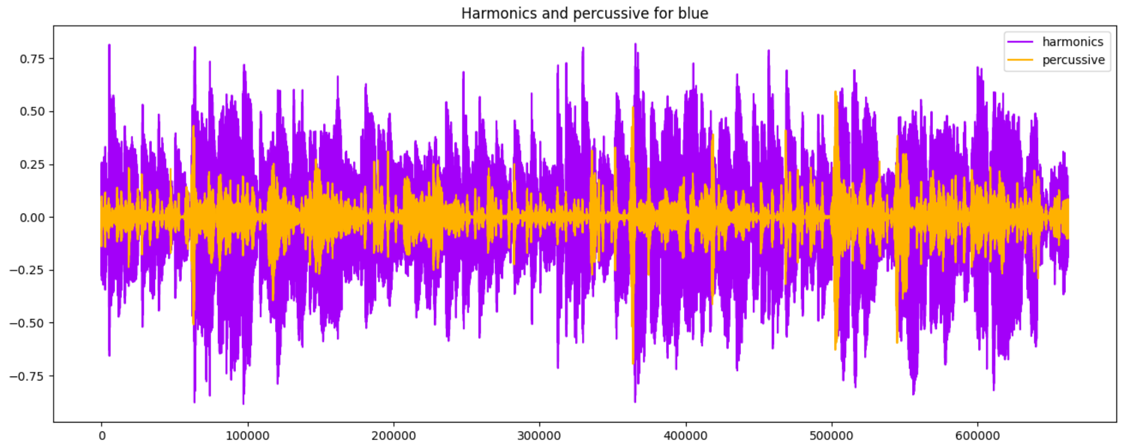
[ ]:
```
y_harm, y_perc = librosa.effects.hpss(y_pop)

plt.figure(figsize = (16, 6))
plt.plot(y_harm, color = '#A300F9', label = 'harmonics');
plt.plot(y_perc, color = '#FFB100', label = 'percussive');
plt.legend()
plt.title('Harmonics and percussive for pop')
```

[ ]:
```
Text(0.5, 1.0, 'Harmonics and percussive for pop')
```



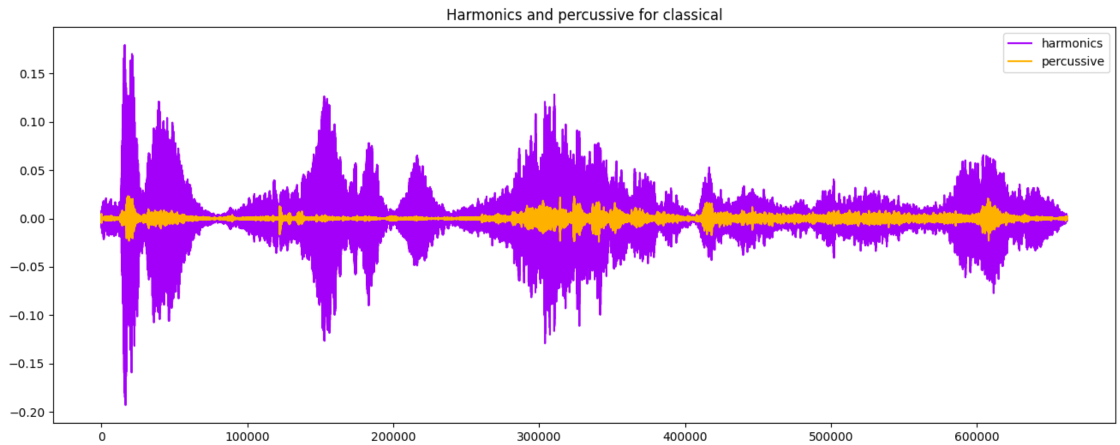
[ ]:
```
y_harm, y_perc = librosa.effects.hpss(y_blue)

plt.figure(figsize = (16, 6))
plt.plot(y_harm, color = '#A300F9', label = 'harmonics');
plt.plot(y_perc, color = '#FFB100', label = 'percussive');
plt.legend()
plt.title('Harmonics and percussive for blue')
```

[ ]:
```
Text(0.5, 1.0, 'Harmonics and percussive for blue')
```




```
[ ]: y_harm, y_perc = librosa.effects.hpss(y_classical)

     plt.figure(figsize = (16, 6))
     plt.plot(y_harm, color = '#A300F9', label = 'harmonics');
     plt.plot(y_perc, color = '#FFB100', label = 'percussive');
     plt.legend()
     plt.title('Harmonics and percussive for classical')
```

```
[ ]: Text(0.5, 1.0, 'Harmonics and percussive for classical')
```



1.1.7 Tempo BMP (beats per minute)

```
[ ]: tempo, _ = librosa.beat.beat_track(y = y_pop, sr = sr_pop)
     tempo
```

[ ]: 99.38401442307692

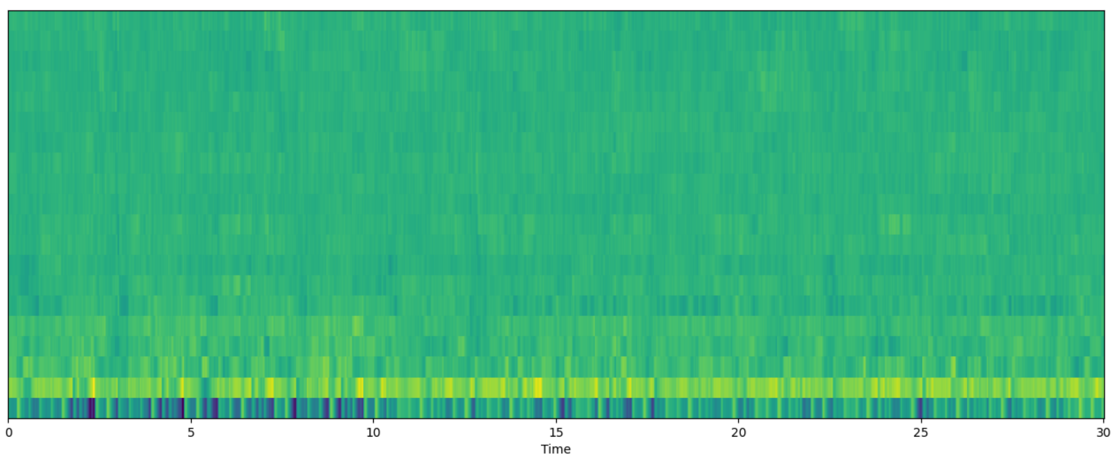
1.1.8 MFCC

A compressed representation of the Mel Spectrograms by the most essential frequency coef.

The x-axis of the MFCCs plot represents time, and the y-axis represents the MFCC coefficient values.

[ ]:
```
mfccs = librosa.feature.mfcc(y = y_pop, sr=sr_pop)
print('mfccs shape:', mfccs.shape)

#Displaying  the MFCCs:
plt.figure(figsize = (16, 6))
librosa.display.specshow(mfccs, sr=sr_pop, x_axis='time', cmap = 'viridis');
```

```
mfccs shape: (20, 1293)
```

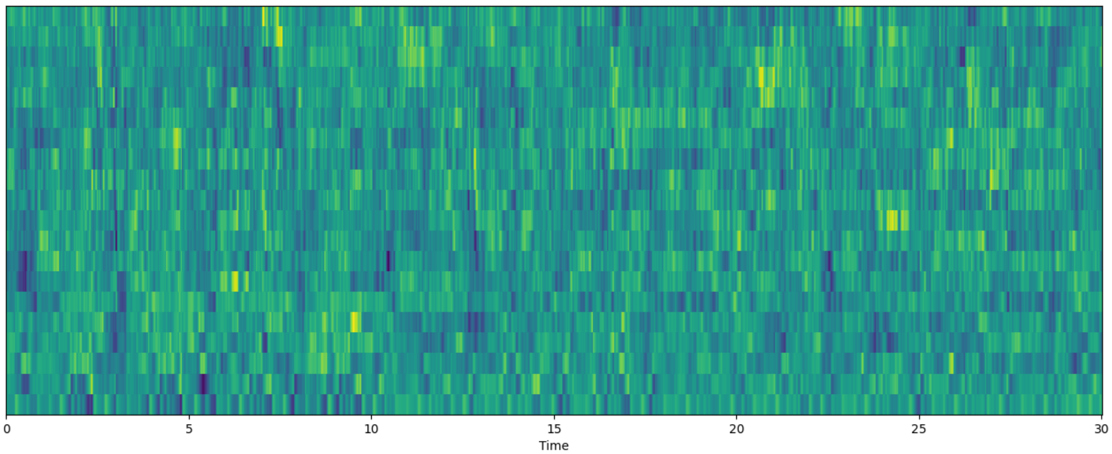


[ ]:
```
# Perform Feature Scaling
mfccs = sklearn.preprocessing.scale(mfccs, axis=1)
print('Mean:', mfccs.mean(), '\n')
print('Var:', mfccs.var())

plt.figure(figsize = (16, 6))
librosa.display.specshow(mfccs, sr=sr_pop, x_axis='time', cmap = 'viridis');
```

```
Mean: -2.360215e-09

Var: 1.0
```

```
/Users/swimmingcircle/miniforge3/envs/tf/lib/python3.9/site-
packages/sklearn/preprocessing/_data.py:240: UserWarning: Numerical issues were
encountered when centering the data and might not be solved. Dataset may contain
too large values. You may need to prescale your features.
```

```
  warnings.warn(
/Users/swimmingcircle/miniforge3/envs/tf/lib/python3.9/site-
packages/sklearn/preprocessing/_data.py:259: UserWarning: Numerical issues were
encountered when scaling the data and might not be solved. The standard
deviation of the data is probably very close to 0.
  warnings.warn(
```




```
[ ]: print(mfccs)
```

```
[[ 0.09206966  0.38610902  0.11332224 …  1.2038206   1.370697
   0.82737654]
 [ 0.26141602  0.34526667  0.451189   …  0.31910515  0.11388601
   0.18868302]
 [ 0.982792    0.8726585   1.0931873  … -0.43070954 -0.5778949
  -0.76126564]
 …
 [-0.32814997 -0.04034512 -0.27681282 …  0.5647969   1.3951571
   2.1499693 ]
 [ 0.73992103  0.7570349  -0.0860804  … -0.20964907  0.44987693
   1.7667273 ]
 [ 0.89229167  0.74019504  0.55440974 … -0.8115252  -1.0920751
  -0.89953953]]
```

1.2 2. EDA

The dataset contains a list of features from the audio files such as spectral centroid (the weighted mean of the frequencies in an audio file). We use this dataset on machine learning methods to predict classification accuracy later on.

```
[ ]: data = pd.read_csv(f'{path}/features_30_sec.csv')
     data.head()
```

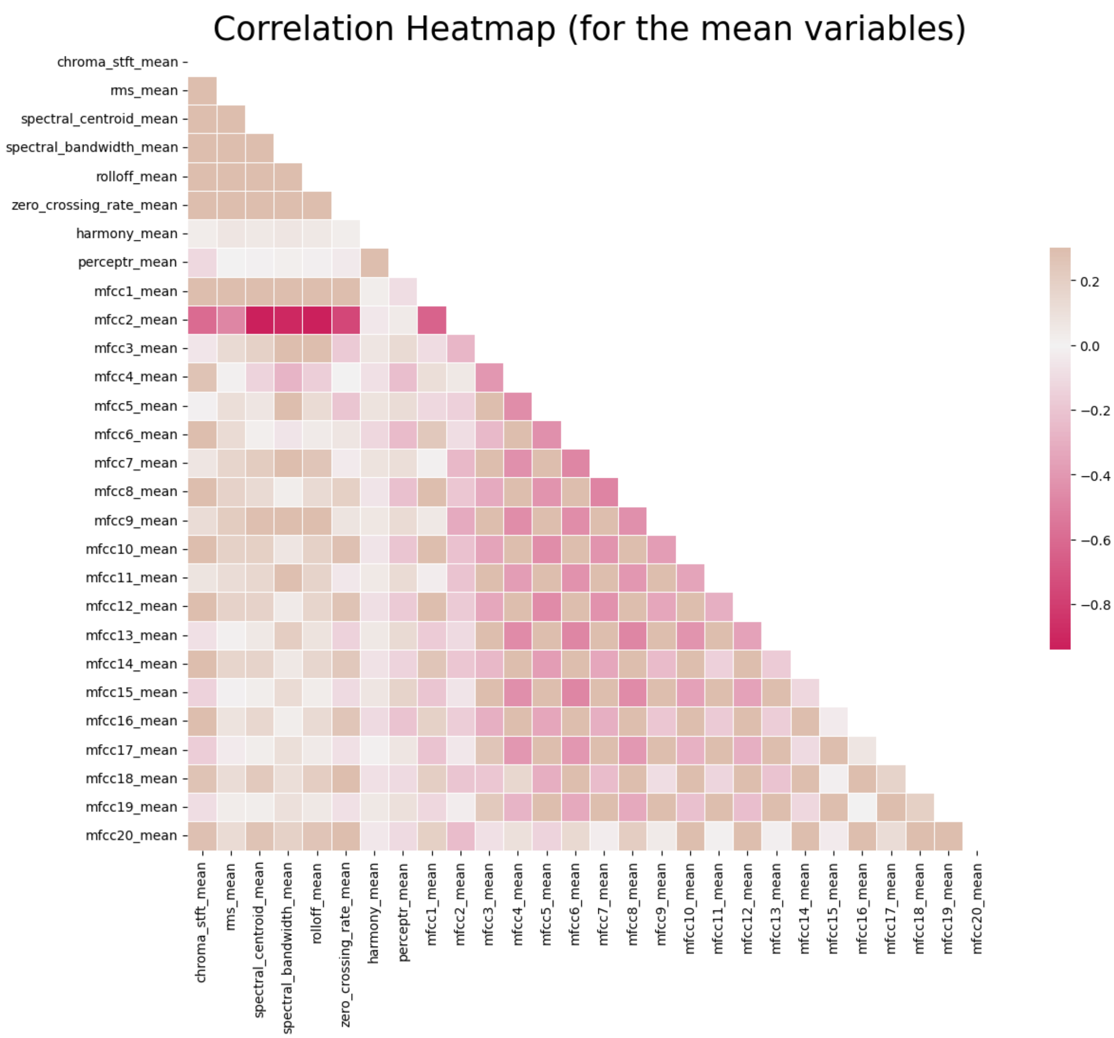
```
[ ]:          filename  length  chroma_stft_mean  chroma_stft_var  rms_mean  \
     0  blues.00000.wav  661794          0.350088         0.088757  0.130228
     1  blues.00001.wav  661794          0.340914         0.094980  0.095948
     2  blues.00002.wav  661794          0.363637         0.085275  0.175570
     3  blues.00003.wav  661794          0.404785         0.093999  0.141093
     4  blues.00004.wav  661794          0.308526         0.087841  0.091529

         rms_var  spectral_centroid_mean  spectral_centroid_var  \
     0  0.002827             1784.165850          129774.064525
     1  0.002373             1530.176679          375850.073649
     2  0.002746             1552.811865          156467.643368
     3  0.006346             1070.106615          184355.942417
     4  0.002303             1835.004266          343399.939274

        spectral_bandwidth_mean  spectral_bandwidth_var  …  mfcc16_var  \
     0              2002.449060            85882.761315  …   52.420910
     1              2039.036516           213843.755497  …   55.356403
     2              1747.702312            76254.192257  …   40.598766
     3              1596.412872           166441.494769  …   44.427753
     4              1748.172116            88445.209036  …   86.099236

        mfcc17_mean  mfcc17_var  mfcc18_mean  mfcc18_var  mfcc19_mean  mfcc19_var  \
     0    -1.690215   36.524071    -0.408979   41.597103    -2.303523   55.062923
     1    -0.731125   60.314529     0.295073   48.120598    -0.283518   51.106190
     2    -7.729093   47.639427    -1.816407   52.382141    -3.439720   46.639660
     3    -3.319597   50.206673     0.636965   37.319130    -0.619121   37.259739
     4    -5.454034   75.269707    -0.916874   53.613918    -4.404827   62.910812

        mfcc20_mean  mfcc20_var  label
     0     1.221291   46.936035  blues
     1     0.531217   45.786282  blues
     2    -2.231258   30.573025  blues
     3    -3.407448   31.949339  blues
     4   -11.703234   55.195160  blues

     [5 rows x 60 columns]
```

1.2.1 Corrrelation heap map

```
[ ]: spike_cols = [col for col in data.columns if 'mean' in col]
     corr = data[spike_cols].corr()

     # Generate a mask for the upper triangle
     mask = np.triu(np.ones_like(corr, dtype=np.bool))

     # Set up the matplotlib figure
     f, ax = plt.subplots(figsize=(16, 11));
```

```python
# Generate a custom diverging colormap
cmap = sns.diverging_palette(0, 25, as_cmap=True, s = 90, l = 45, n = 5)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})

plt.title('Correlation Heatmap (for the mean variables)', fontsize = 25)
plt.xticks(fontsize = 10)
plt.yticks(fontsize = 10);
```

```
/var/folders/0h/xyv81g2n7sj6zr0c9cw30gkc0000gn/T/ipykernel_81575/4060137719.py:5
: DeprecationWarning: `np.bool` is a deprecated alias for the builtin `bool`. To
silence this warning, use `bool` by itself. Doing this will not modify any
behavior and is safe. If you specifically wanted the numpy scalar type, use
`np.bool_` here.
Deprecated in NumPy 1.20; for more details and guidance:
https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  mask = np.triu(np.ones_like(corr, dtype=np.bool))
```



It seems that chroma sfft mean, rms mean, spectral centriod mean, spectral bandwidth mean, rolloff mean zero cross rating mean seems to be the most meaningul variables with the strongest correlation relates to each other.

1.2.2 PCA

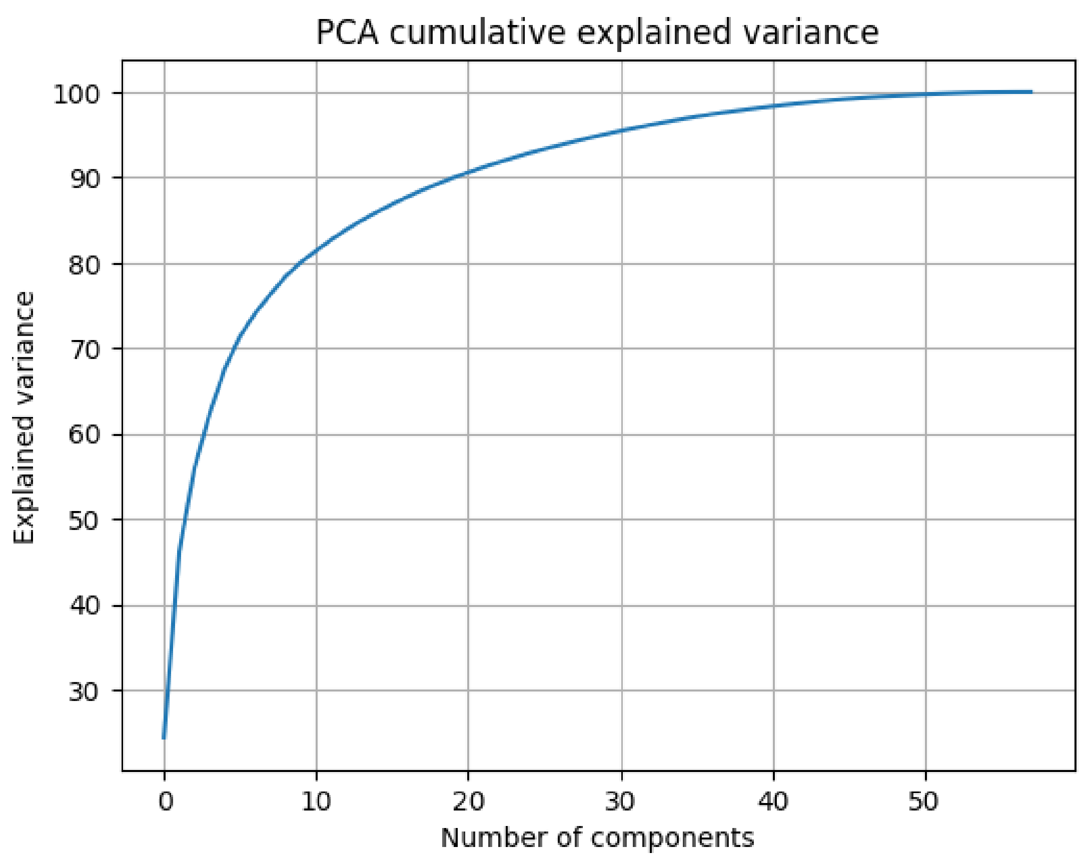
Since there are lots of similarities among features, we use PCA to condese the features and examine the possiblities for classification through componennts.

[ ]:
```
from sklearn import preprocessing


data = data.drop(['filename'], axis=1)
y = data['label']
X = data.loc[:, data.columns != 'label']
```

```
#### NORMALIZE X ####
cols = X.columns
min_max_scaler = preprocessing.MinMaxScaler()
np_scaled = min_max_scaler.fit_transform(X)
X = pd.DataFrame(np_scaled, columns = cols)
```

[ ]:
```
import numpy as np
from sklearn.decomposition import PCA
# Use 100 components to see explained variance

pca_58 = PCA(n_components = 58)
pca_58.fit(X)

plt.grid()
plt.plot(np.cumsum(pca_58.explained_variance_ratio_ * 100))
plt.xlabel('Number of components')
plt.ylabel('Explained variance')
plt.title('PCA cumulative explained variance')
```

[ ]:
```
Text(0.5, 1.0, 'PCA cumulative explained variance')
```



[ ]:
```python
import pandas as pd
explained_var = np.cumsum(pca_58.explained_variance_ratio_ * 100).reshape(-1, 1)
num_comps = [i+1 for i in range(58)]
explained_var
explained_var_df = pd.DataFrame(explained_var,index=num_comps, columns =
 ↪['Explained Variance Ratio'])
explained_var_df
```

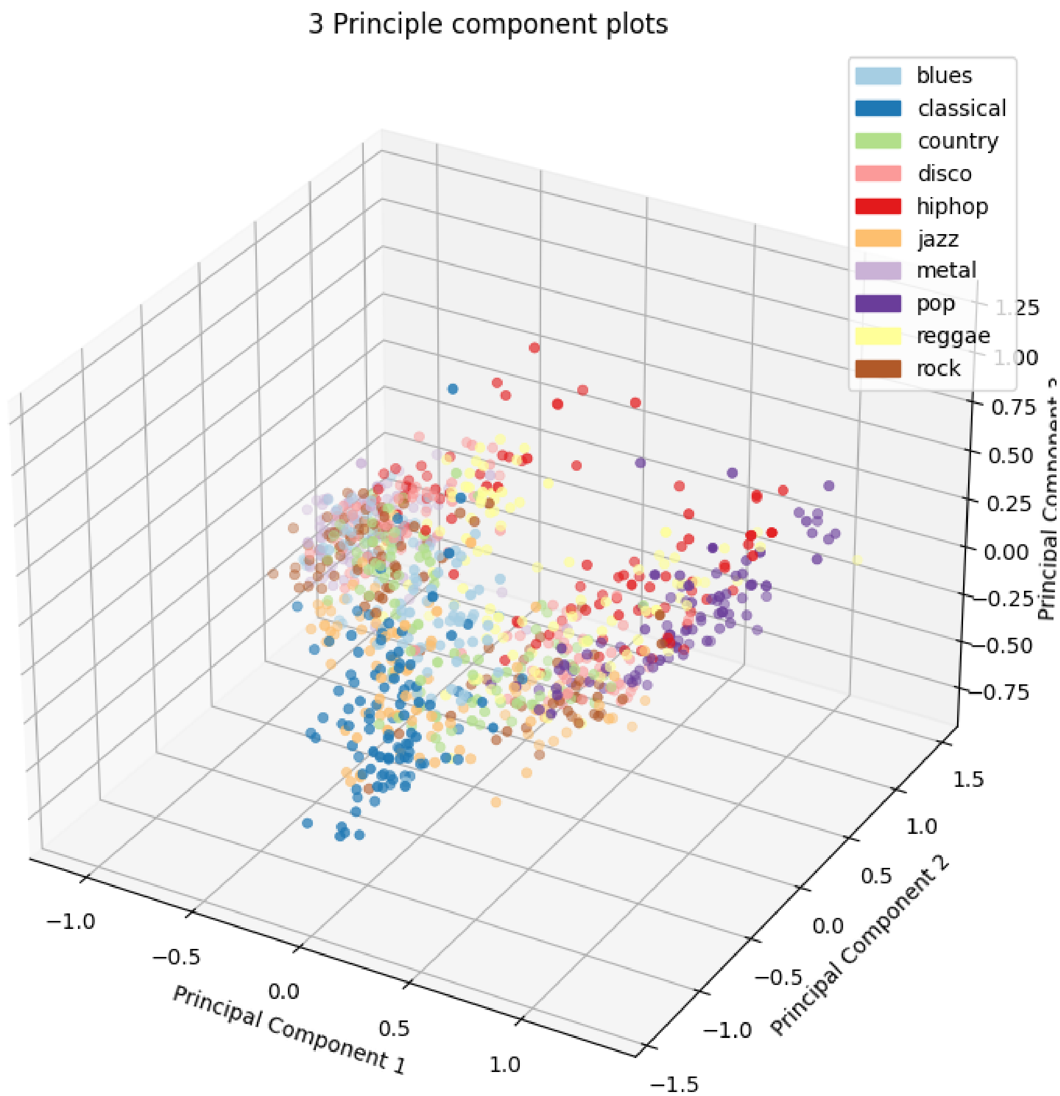
[ ]:

	Explained Variance Ratio
1	24.393550
2	46.175354
3	55.869008
4	62.307090
5	67.594676
6	71.390181
7	74.093713
8	76.294254
9	78.407186
10	80.051094
11	81.390982
12	82.698649
13	83.880329
14	84.954229
15	85.927882
16	86.847171
17	87.707583
18	88.511371
19	89.239098
20	89.931975
21	90.574360
22	91.190001
23	91.759817
24	92.303727
25	92.819800
26	93.305670
27	93.770106
28	94.209590
29	94.638690
30	95.042563
31	95.431485
32	95.789835
33	96.142766
34	96.481475
35	96.805725
36	97.114400
37	97.394488
38	97.642221

39	97.882790
40	98.111695
41	98.317939
42	98.519024
43	98.706679
44	98.889972
45	99.052849
46	99.198941
47	99.334579
48	99.445599
49	99.536310
50	99.624271
51	99.709509
52	99.787073
53	99.856644
54	99.918138
55	99.958835
56	99.977609
57	99.993447
58	100.000000

[ ]:
```
from mpl_toolkits import mplot3d
from sklearn.preprocessing import LabelEncoder


pca = PCA(n_components=3)
principalComponents = pca.fit_transform(X)
principalDf = pd.DataFrame(data = principalComponents, columns = ['principal␣
↪component 1', 'principal component 2', 'principal component 3'])

# concatenate with target label
finalDf = pd.concat([principalDf, y], axis = 1)

# Define an array of color names
le = LabelEncoder()
color_numbers = le.fit_transform(finalDf["label"])

fig = plt.figure(figsize = (16, 9))
ax = fig.add_subplot(projection='3d')
ax.scatter(finalDf["principal component 1"], finalDf["principal component 2"],␣
↪finalDf["principal component 3"],c = color_numbers, cmap='Paired',␣
↪linewidth=0.5)

# Add labels and title
ax.set_xlabel('Principal Component 1')
ax.set_ylabel('Principal Component 2')
ax.set_zlabel('Principal Component 3')
```

```
ax.set_title('3 Principle component plots')

# Find the label names and corresponding color codes
label_names = le.classes_
color_codes = plt.get_cmap('Paired')(np.linspace(0, 1, len(label_names)))

# Create a legend
legend_handles = [plt.Rectangle((0,0),1,1, color=color_codes[i], label=label_names[i]) for i in range(len(label_names))]
ax.legend(handles=legend_handles)

plt.show()
```



We can see that there are some patterns but it's not clearly visible to classify different types of music using thre components.

1.3 3. Classification through feature data

1.3.1 1D CNN classification

We cannot use 2D CNN classifier because of the small amount of features that are extracted from the audio dataset.

[ ]:
```
import IPython.display as ipd
import librosa.display

import tensorflow as tf
import tensorflow.keras as keras

from tensorflow.keras import Sequential
from tensorflow.keras.layers import Conv2D

import sklearn.model_selection as sk

from sklearn.model_selection import train_test_split
```

[ ]:
```
y = data['label'] # genre variable.
X = data.loc[:, data.columns != 'label'] #select all columns but not the labels

#### NORMALIZE X ####
# Normalize so everything is on the same scale.
cols = X.columns
min_max_scaler = preprocessing.MinMaxScaler()
np_scaled = min_max_scaler.fit_transform(X)

# new data frame with the new scaled data.
X = pd.DataFrame(np_scaled, columns = cols)
```

[ ]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)
```

[ ]:
```
from sklearn.preprocessing import LabelEncoder

label_encoder = LabelEncoder()
y_train = label_encoder.fit_transform(y_train)
y_test = label_encoder.fit_transform(y_test)
```

[ ]:
```
X_train = np.asarray(X_train).reshape((X_train.shape[0], X_train.shape[1], 1))
X_test = np.asarray(X_test).reshape((X_test.shape[0], X_test.shape[1], 1))

# Define the CNN model
```

```python
model = keras.Sequential([
    keras.layers.Conv1D(32, kernel_size=3, activation='relu',␣
 ↪input_shape=X_train.shape[1:]),
    keras.layers.MaxPooling1D(pool_size=2),
    keras.layers.Conv1D(32, kernel_size=3, activation='relu'),
    keras.layers.MaxPooling1D(pool_size=2),
    keras.layers.Flatten(),
    keras.layers.Dense(10, activation='softmax')
])

# Compile the model and train it on the input data
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy',␣
 ↪metrics=['accuracy'])
history = model.fit(X_train, y_train, epochs=20, batch_size=32,␣
 ↪validation_data=(X_test, y_test))
```

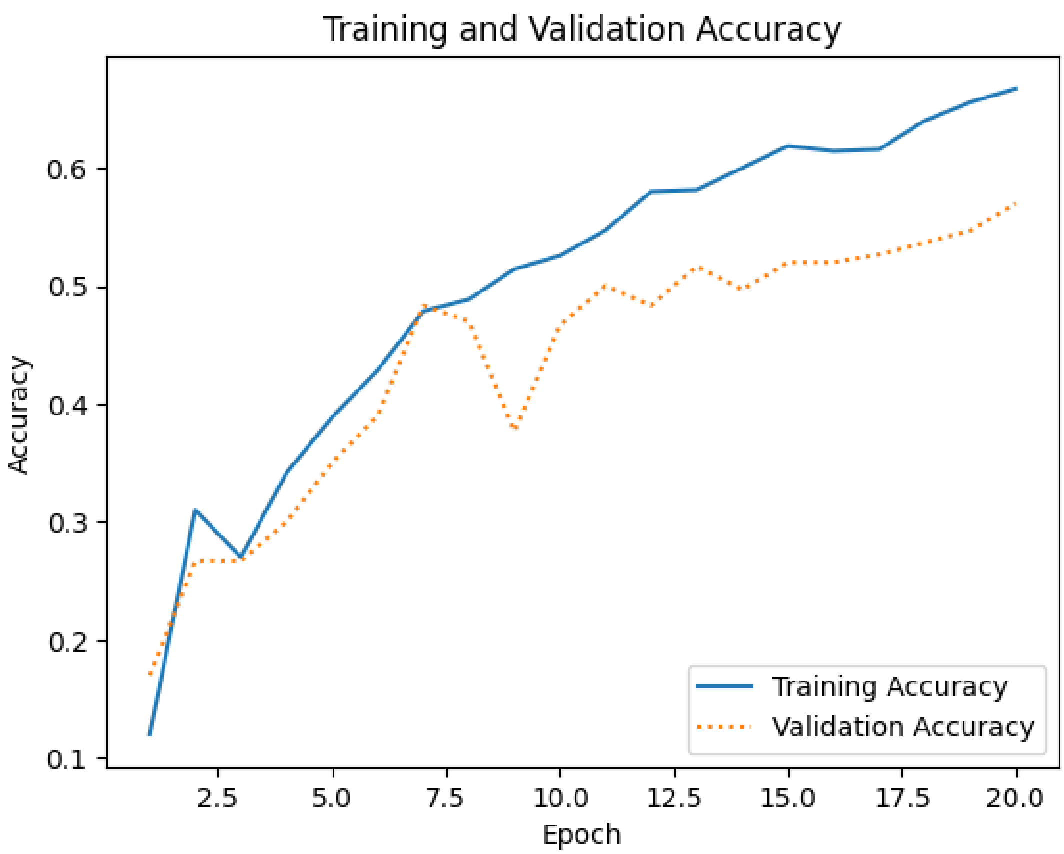
```
Epoch 1/20

2023-04-16 20:38:46.031905: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.

22/22 [==============================] - ETA: 0s - loss: 2.2839 - accuracy:
0.1200

2023-04-16 20:38:47.090227: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.

22/22 [==============================] - 2s 48ms/step - loss: 2.2839 - accuracy:
0.1200 - val_loss: 2.2835 - val_accuracy: 0.1700
Epoch 2/20
 1/22 [>…] - ETA: 0s - loss: 2.2362 - accuracy:
0.4062Epoch 2/20
22/22 [==============================] - 0s 10ms/step - loss: 2.2424 - accuracy:
0.3100 - val_loss: 2.2442 - val_accuracy: 0.2667
Epoch 3/20
22/22 [==============================] - 0s 10ms/step - loss: 2.1792 - accuracy:
0.2700 - val_loss: 2.1701 - val_accuracy: 0.2667
Epoch 4/20
22/22 [==============================] - 0s 11ms/step - loss: 2.0734 - accuracy:
0.3414 - val_loss: 2.0739 - val_accuracy: 0.3000
Epoch 5/20
22/22 [==============================] - 0s 8ms/step - loss: 1.9246 - accuracy:
0.3886 - val_loss: 1.9275 - val_accuracy: 0.3500
Epoch 6/20
22/22 [==============================] - 0s 11ms/step - loss: 1.7557 - accuracy:
0.4286 - val_loss: 1.8002 - val_accuracy: 0.3900
Epoch 7/20
```

```
22/22 [==============================] - 0s 8ms/step - loss: 1.6009 - accuracy:
0.4786 - val_loss: 1.6542 - val_accuracy: 0.4833
Epoch 8/20
22/22 [==============================] - 0s 8ms/step - loss: 1.4930 - accuracy:
0.4886 - val_loss: 1.5844 - val_accuracy: 0.4700
Epoch 9/20
22/22 [==============================] - 0s 9ms/step - loss: 1.4155 - accuracy:
0.5143 - val_loss: 1.5798 - val_accuracy: 0.3767
Epoch 10/20
22/22 [==============================] - 0s 9ms/step - loss: 1.3650 - accuracy:
0.5257 - val_loss: 1.4907 - val_accuracy: 0.4667
Epoch 11/20
22/22 [==============================] - 0s 8ms/step - loss: 1.2868 - accuracy:
0.5471 - val_loss: 1.4481 - val_accuracy: 0.5000
Epoch 12/20
22/22 [==============================] - 0s 8ms/step - loss: 1.2369 - accuracy:
0.5800 - val_loss: 1.4303 - val_accuracy: 0.4833
Epoch 13/20
22/22 [==============================] - 0s 8ms/step - loss: 1.1989 - accuracy:
0.5814 - val_loss: 1.3690 - val_accuracy: 0.5167
Epoch 14/20
22/22 [==============================] - 0s 8ms/step - loss: 1.1689 - accuracy:
0.6000 - val_loss: 1.3614 - val_accuracy: 0.4967
Epoch 15/20
22/22 [==============================] - 0s 10ms/step - loss: 1.1279 - accuracy:
0.6186 - val_loss: 1.3259 - val_accuracy: 0.5200
Epoch 16/20
22/22 [==============================] - 0s 8ms/step - loss: 1.1049 - accuracy:
0.6143 - val_loss: 1.3321 - val_accuracy: 0.5200
Epoch 17/20
22/22 [==============================] - 0s 9ms/step - loss: 1.0814 - accuracy:
0.6157 - val_loss: 1.3241 - val_accuracy: 0.5267
Epoch 18/20
22/22 [==============================] - 0s 9ms/step - loss: 1.0446 - accuracy:
0.6400 - val_loss: 1.2927 - val_accuracy: 0.5367
Epoch 19/20
22/22 [==============================] - 0s 10ms/step - loss: 1.0257 - accuracy:
0.6557 - val_loss: 1.2981 - val_accuracy: 0.5467
Epoch 20/20
22/22 [==============================] - 0s 8ms/step - loss: 0.9927 - accuracy:
0.6671 - val_loss: 1.2353 - val_accuracy: 0.5700
```

[ ]:
```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
epochs = range(1, len(acc) + 1)

plt.plot(epochs, acc, '-', label='Training Accuracy')
```

```
plt.plot(epochs, val_acc, ':', label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')
```

[ ]: <matplotlib.legend.Legend at 0x381033d30>



1.3.2 Logistic Regression

[ ]:
```
X_train = X_train.reshape(X_train.shape[0], X_train.shape[1])
X_test = X_test.reshape(X_test.shape[0], X_test.shape[1])

from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report

# Logistic Regression
lg = LogisticRegression(random_state=0, solver='lbfgs',␣
 ↪multi_class='multinomial')
```

```
lg.fit(X_train, y_train)
y_pred = lg.predict(X_test)

cr = classification_report(y_test, y_pred)
print(cr)
```

```
              precision    recall  f1-score   support

           0       0.46      0.46      0.46        35
           1       0.87      1.00      0.93        20
           2       0.70      0.51      0.59        37
           3       0.65      0.44      0.53        34
           4       0.63      0.71      0.67        24
           5       0.87      0.79      0.83        33
           6       0.53      0.90      0.67        30
           7       0.66      0.83      0.73        23
           8       0.50      0.52      0.51        29
           9       0.48      0.34      0.40        35

    accuracy                           0.62       300
   macro avg       0.63      0.65      0.63       300
weighted avg       0.63      0.62      0.61       300


/Users/swimmingcircle/miniforge3/envs/tf/lib/python3.9/site-
packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

1.3.3 MLP classifier

[ ]:
```
from sklearn.neural_network import MLPClassifier

# Neural Nets
nn = MLPClassifier(solver='lbfgs', alpha=1e-5, hidden_layer_sizes=(5000, 10),␣
 ↪random_state=1)
nn.fit(X_train, y_train)
y_pred = nn.predict(X_test)

cr = classification_report(y_test, y_pred)
```

```
print(cr)
```

```
              precision    recall  f1-score   support

           0       0.64      0.66      0.65        35
           1       0.86      0.90      0.88        20
           2       0.43      0.24      0.31        37
           3       0.36      0.38      0.37        34
           4       0.54      0.79      0.64        24
           5       0.81      0.67      0.73        33
           6       0.73      0.80      0.76        30
           7       0.85      0.74      0.79        23
           8       0.48      0.48      0.48        29
           9       0.40      0.49      0.44        35

    accuracy                           0.59       300
   macro avg       0.61      0.61      0.61       300
weighted avg       0.59      0.59      0.58       300
```

```
/Users/swimmingcircle/miniforge3/envs/tf/lib/python3.9/site-
packages/sklearn/neural_network/_multilayer_perceptron.py:541:
ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
  self.n_iter_ = _check_optimize_result("lbfgs", opt_res, self.max_iter)
```

1.3.4 XGboost classifer

[ ]:
```
from xgboost import XGBClassifier, XGBRFClassifier
from xgboost import plot_tree, plot_importance

# Cross Gradient Booster
xgb = XGBClassifier(n_estimators=1000, learning_rate=0.05)
xgb.fit(X_train, y_train)
y_pred = xgb.predict(X_test)

cr = classification_report(y_test, y_pred)
print(cr)
```

```
              precision    recall  f1-score   support

           0       0.81      0.71      0.76        35
           1       0.87      1.00      0.93        20
           2       0.79      0.70      0.74        37
           3       0.76      0.56      0.64        34
           4       0.59      0.83      0.69        24
```

```
           5       0.93      0.82      0.87        33
           6       0.69      0.90      0.78        30
           7       0.72      0.91      0.81        23
           8       0.68      0.59      0.63        29
           9       0.59      0.54      0.57        35

    accuracy                           0.74       300
   macro avg       0.74      0.76      0.74       300
weighted avg       0.74      0.74      0.73       300
```

Comparing the accuracy: - XGBoost: 0.74 - Logistic: 0.62 - MLP: 0.59 - 1D CNN: 0.5

We found that XGBoost has the best performance using the feature extracted dataset.

1.4 4. Classification through audio images

[ ]:
```
import tensorflow as tf
tf.config.experimental.list_physical_devices('GPU')
```

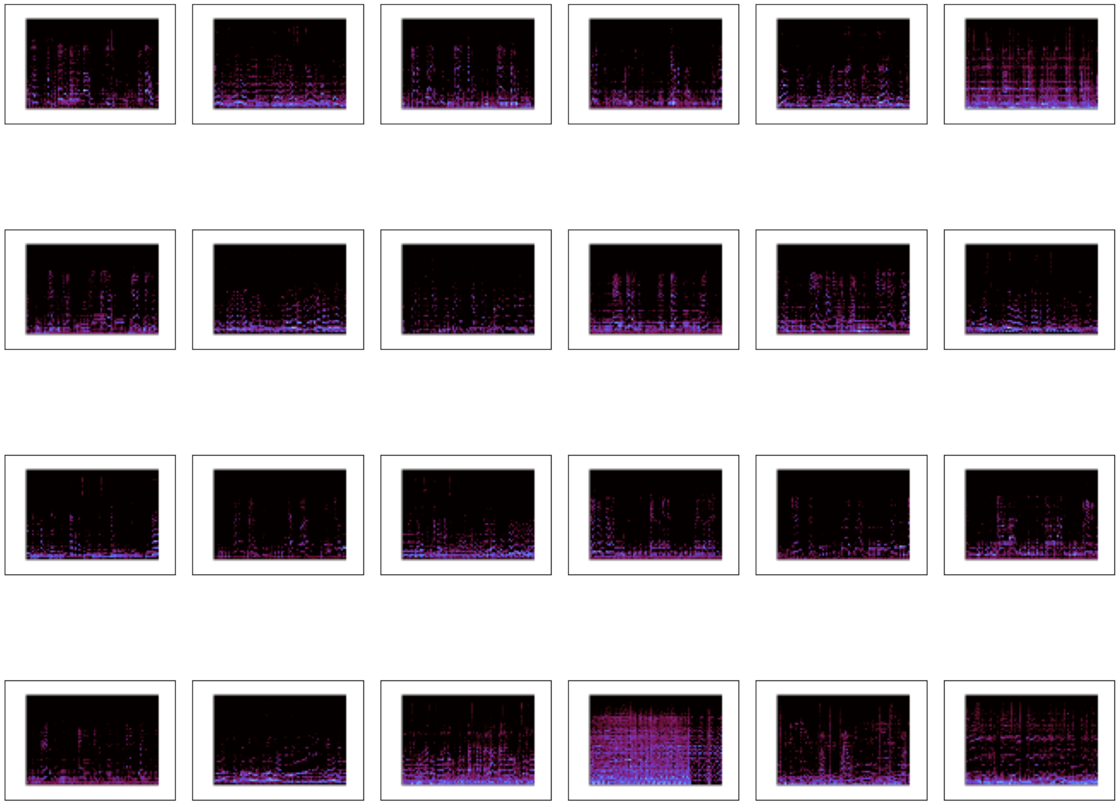
[ ]:
```
[PhysicalDevice(name='/physical_device:GPU:0', device_type='GPU')]
```

[ ]:
```
import os
from glob import glob
from PIL import Image
import cv2
import os
from sklearn.model_selection import train_test_split
from sklearn.svm import LinearSVC
import tensorflow as tf
from tensorflow import keras
from sklearn.metrics import classification_report
# from resizeimage import resizeimage
import numpy as np
import matplotlib.pyplot as plt
```

[ ]:
```
input_dir = 'GTZAN/images_original/'

# Define input directory
def process_images(path):
    images = []
    flattened = []
    # Loop over all images in input directory
    for filename in os.listdir(path):
        # Load image
        image_path = os.path.join(path, filename)
        image = cv2.imread(image_path)
        # print(image.shape)
```

```python
        resize = cv2.resize(image, (100, 70))
        images.append(resize)
        flattened.append(np.array(resize).flatten())
    X = np.asarray(flattened)
    return images, flattened, X


def process_categories(input_dir):
    X_categories = []
    y_labels = []


    for i,subdir in enumerate(os.listdir(input_dir)):
        images, flattened, X = process_images(os.path.join(input_dir, subdir))
        X_categories.append(X)
        y_labels.append(np.full(len(X), i))
    X = np.vstack(X_categories)
    y = np.concatenate(y_labels)
    return X, y


X, y = process_categories(input_dir)
```

[ ]:
```python
blue_dir = 'GTZAN/images_original/blues'
images_blue, flattened_blue , X_blue = process_images(blue_dir)

#plot the photos
def original_photos(images):
    fig, ax = plt.subplots(4, 6, figsize=(20, 16),
                        subplot_kw={'xticks':[], 'yticks':[]},
                        gridspec_kw=dict(hspace=0.1, wspace=0.1))

    k = 0
    for i in range(4):
        for j in range(6):
            ax[i, j].imshow(images[k])
            k += 1

    plt.show()
original_photos(images_blue)
```



```
[ ]: #train test split
X_train,X_test,y_train,y_test = train_test_split(X, y, test_size=0.20, random_state=123)
print(f'There are {len(X_train)} training images, and {len(X_test)} testing images.' )
```

```
There are 799 training images, and 200 testing images.
```

1.5 Logisitc Regression: baseline analysis

```
[ ]: from sklearn.linear_model import LogisticRegression
     from sklearn.metrics import classification_report

     # Logistic Regression
     lg = LogisticRegression(random_state=0, solver='lbfgs',␣
      ↪multi_class='multinomial')

     lg.fit(X_train, y_train)
     y_pred = lg.predict(X_test)

     cr = classification_report(y_test, y_pred)
     print(cr)
```

```
              precision    recall  f1-score   support

           0       0.39      0.67      0.49        18
           1       0.79      0.62      0.70        24
           2       0.24      0.24      0.24        17
           3       0.58      0.54      0.56        28
           4       0.30      0.46      0.36        13
           5       0.89      0.53      0.67        15
           6       0.27      0.39      0.32        18
           7       0.54      0.35      0.42        20
           8       0.41      0.46      0.43        24
           9       0.75      0.39      0.51        23

    accuracy                           0.47       200
   macro avg       0.51      0.46      0.47       200
weighted avg       0.53      0.47      0.48       200


/Users/swimmingcircle/miniforge3/envs/tf/lib/python3.9/site-
packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

1.6 MLP Classifier

MLP classifier doesn't able to run.

```
[ ]: # from sklearn.neural_network import MLPClassifier

# # Neural Nets
# nn = MLPClassifier(solver='lbfgs', alpha=1e-5, hidden_layer_sizes=(5000, 10),␣
 ↪random_state=1)
# nn.fit(X_train, y_train)
# y_pred = nn.predict(X_test)

# cr = classification_report(y_test, y_pred)
# print(cr)
```

1.7 Linear SVC

```
[ ]: svc = LinearSVC(verbose=0).fit(X_train, y_train)

score = svc.score(X_train, y_train)
print("Score: ", score)

#prediction
y_pred = svc.predict(X_test)

cr = classification_report(y_test, y_pred)
print(cr)
```

```
Score:  0.9987484355444305
              precision    recall  f1-score   support

           0       0.42      0.56      0.48        18
           1       0.72      0.75      0.73        24
           2       0.25      0.24      0.24        17
           3       0.47      0.32      0.38        28
           4       0.25      0.31      0.28        13
           5       0.43      0.60      0.50        15
           6       0.25      0.28      0.26        18
           7       0.36      0.25      0.29        20
           8       0.36      0.38      0.37        24
           9       0.50      0.43      0.47        23

    accuracy                           0.41       200
   macro avg       0.40      0.41      0.40       200
weighted avg       0.42      0.41      0.41       200

/Users/swimmingcircle/miniforge3/envs/tf/lib/python3.9/site-
packages/sklearn/svm/_base.py:1244: ConvergenceWarning: Liblinear failed to
converge, increase the number of iterations.
  warnings.warn(
```

1.8 CNN

[ ]:
```
X_train.shape
```

[ ]:
```
(799, 21000)
```

[ ]:
```
import numpy as np
X_train_reshaped = np.reshape(X_train, (X_train.shape[0], 100, 70, 3))
X_test_reshaped = np.reshape(X_test, (X_test.shape[0], 100, 70, 3))

# X_train_reshaped = np.reshape(X_train, (X_train.shape[0], 432, 288, 3))
# X_test_reshaped = np.reshape(X_test, (X_test.shape[0], 432, 288, 3))
X_train_reshaped.shape, X_test_reshaped.shape
```

[ ]:
```
((799, 100, 70, 3), (200, 100, 70, 3))
```

[ ]:
```
import numpy as np

# Reshape x_train to a 4D tensor
height = 100
width = 70
channels = 3

# Convert x_train to float32 data type and normalize the pixel values to [0, 1]
X_train_reshaped = X_train_reshaped.astype(np.float32) / 255.0
X_test_reshaped = X_test_reshaped.astype(np.float32) / 255.0
y_train_reshaped = y_train.reshape(-1,1)
y_test_reshaped = y_test.reshape(-1,1)
```

[ ]:
```
import tensorflow as tf

# Define input shape
input_shape = (height, width, channels)

# Define model
model1 = keras.Sequential([
    keras.layers.Conv2D(32, kernel_size=(3, 3), activation='relu',␣
 ↪input_shape=input_shape),
    keras.layers.MaxPooling2D(pool_size=(2, 2)),
    keras.layers.Flatten(),
    keras.layers.Dense(216, activation='relu'),
    keras.layers.Dropout(0.2),
    keras.layers.Dense(10, activation='softmax')
])

# Compile model
model1.compile(optimizer='adam', loss='categorical_crossentropy',␣
 ↪metrics=['accuracy'])
```

```python
# Print model summary
model1.summary()
```

```
Model: "sequential_36"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_60 (Conv2D)          (None, 98, 68, 32)        896

 max_pooling2d_54 (MaxPoolin  (None, 49, 34, 32)       0
 g2D)

 flatten_37 (Flatten)        (None, 53312)             0

 dense_92 (Dense)            (None, 216)               11515608

 dropout_56 (Dropout)        (None, 216)               0

 dense_93 (Dense)            (None, 10)                2170

=================================================================
Total params: 11,518,674
Trainable params: 11,518,674
Non-trainable params: 0
_________________________________________________________________
```


```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_60 (Conv2D)          (None, 98, 68, 32)        896

 max_pooling2d_54 (MaxPoolin  (None, 49, 34, 32)       0
 g2D)

 flatten_37 (Flatten)        (None, 53312)             0

 dense_92 (Dense)            (None, 216)               11515608

 dropout_56 (Dropout)        (None, 216)               0

 dense_93 (Dense)            (None, 10)                2170

=================================================================
Total params: 11,518,674
Trainable params: 11,518,674
Non-trainable params: 0
_________________________________________________________________
```

[ ]:
```python
from keras.utils import to_categorical

y_train_one_hot = to_categorical(y_train_reshaped)
y_test_one_hot = to_categorical(y_test_reshaped)
```

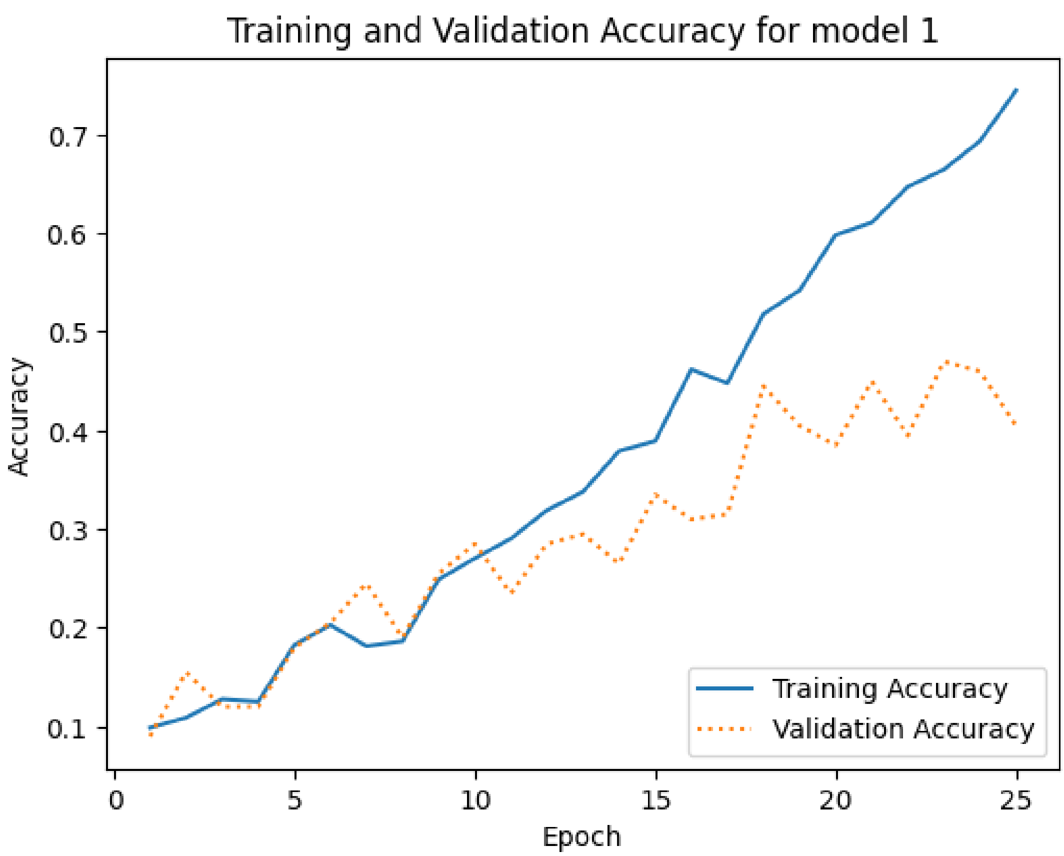
[ ]:
```python
history1 = model1.fit(X_train_reshaped, y_train_one_hot, epochs=25,␣
    ↪validation_data=(X_test_reshaped, y_test_one_hot))
```

```
Epoch 1/25

2023-04-16 19:45:03.906596: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.

25/25 [==============================] - ETA: 0s - loss: 4.9602 - accuracy:
0.0989

2023-04-16 19:45:05.676026: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.

25/25 [==============================] - 2s 71ms/step - loss: 4.9602 - accuracy:
0.0989 - val_loss: 2.3149 - val_accuracy: 0.0900
Epoch 2/25
Epoch 2/25
25/25 [==============================] - 1s 44ms/step - loss: 2.2831 - accuracy:
0.1089 - val_loss: 2.2716 - val_accuracy: 0.1550
Epoch 3/25
25/25 [==============================] - 1s 43ms/step - loss: 2.2654 - accuracy:
0.1277 - val_loss: 2.2515 - val_accuracy: 0.1200
Epoch 4/25
25/25 [==============================] - 1s 42ms/step - loss: 2.2073 - accuracy:
0.1252 - val_loss: 2.2227 - val_accuracy: 0.1200
Epoch 5/25
25/25 [==============================] - 1s 42ms/step - loss: 2.1815 - accuracy:
0.1827 - val_loss: 2.1425 - val_accuracy: 0.1800
Epoch 6/25
25/25 [==============================] - 1s 44ms/step - loss: 2.1531 - accuracy:
0.2028 - val_loss: 2.1401 - val_accuracy: 0.2050
Epoch 7/25
25/25 [==============================] - 1s 44ms/step - loss: 2.1339 - accuracy:
0.1815 - val_loss: 2.0889 - val_accuracy: 0.2450
Epoch 8/25
25/25 [==============================] - 1s 41ms/step - loss: 2.0557 - accuracy:
0.1865 - val_loss: 2.0710 - val_accuracy: 0.1900
Epoch 9/25
25/25 [==============================] - 1s 43ms/step - loss: 2.0235 - accuracy:
0.2491 - val_loss: 2.0074 - val_accuracy: 0.2550
Epoch 10/25
25/25 [==============================] - 1s 41ms/step - loss: 1.9714 - accuracy:
```

```
0.2703 - val_loss: 1.9570 - val_accuracy: 0.2850
Epoch 11/25
25/25 [==============================] - 1s 42ms/step - loss: 1.8889 - accuracy:
0.2904 - val_loss: 1.9128 - val_accuracy: 0.2350
Epoch 12/25
25/25 [==============================] - 1s 42ms/step - loss: 1.8125 - accuracy:
0.3191 - val_loss: 1.8602 - val_accuracy: 0.2850
Epoch 13/25
25/25 [==============================] - 1s 42ms/step - loss: 1.7875 - accuracy:
0.3379 - val_loss: 1.8296 - val_accuracy: 0.2950
Epoch 14/25
25/25 [==============================] - 1s 41ms/step - loss: 1.7034 - accuracy:
0.3792 - val_loss: 1.9135 - val_accuracy: 0.2650
Epoch 15/25
25/25 [==============================] - 1s 42ms/step - loss: 1.6393 - accuracy:
0.3892 - val_loss: 1.7601 - val_accuracy: 0.3350
Epoch 16/25
25/25 [==============================] - 1s 41ms/step - loss: 1.5424 - accuracy:
0.4618 - val_loss: 1.7579 - val_accuracy: 0.3100
Epoch 17/25
25/25 [==============================] - 1s 42ms/step - loss: 1.5447 - accuracy:
0.4481 - val_loss: 1.6982 - val_accuracy: 0.3150
Epoch 18/25
25/25 [==============================] - 1s 41ms/step - loss: 1.3669 - accuracy:
0.5181 - val_loss: 1.6034 - val_accuracy: 0.4450
Epoch 19/25
25/25 [==============================] - 1s 42ms/step - loss: 1.3153 - accuracy:
0.5419 - val_loss: 1.6054 - val_accuracy: 0.4050
Epoch 20/25
25/25 [==============================] - 1s 43ms/step - loss: 1.2225 - accuracy:
0.5982 - val_loss: 1.6541 - val_accuracy: 0.3850
Epoch 21/25
25/25 [==============================] - 1s 42ms/step - loss: 1.1374 - accuracy:
0.6108 - val_loss: 1.5364 - val_accuracy: 0.4500
Epoch 22/25
25/25 [==============================] - 1s 42ms/step - loss: 1.0269 - accuracy:
0.6471 - val_loss: 1.5674 - val_accuracy: 0.3950
Epoch 23/25
25/25 [==============================] - 2s 70ms/step - loss: 0.9930 - accuracy:
0.6646 - val_loss: 1.5558 - val_accuracy: 0.4700
Epoch 24/25
25/25 [==============================] - 1s 44ms/step - loss: 0.9360 - accuracy:
0.6934 - val_loss: 1.4904 - val_accuracy: 0.4600
Epoch 25/25
25/25 [==============================] - 1s 42ms/step - loss: 0.8280 - accuracy:
0.7447 - val_loss: 1.5228 - val_accuracy: 0.4050
```

[ ]:
```
acc = history1.history['accuracy']
val_acc = history1.history['val_accuracy']
epochs = range(1, len(acc) + 1)

plt.plot(epochs, acc, '-', label='Training Accuracy')
plt.plot(epochs, val_acc, ':', label='Validation Accuracy')
plt.title('Training and Validation Accuracy for model 1')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')
```

[ ]: <matplotlib.legend.Legend at 0x2db138a90>



[ ]:
```
from keras.layers import LeakyReLU

# Define model
reg_param = 0.001


model2 = keras.Sequential([
```

```
    keras.layers.Conv2D(64, kernel_size=(3, 3), input_shape=input_shape),
    LeakyReLU(alpha=0.1),
    keras.layers.MaxPooling2D(pool_size=(2, 2)),
    keras.layers.Flatten(),
    keras.layers.Dense(216),
    LeakyReLU(alpha=0.1),
    keras.layers.Dropout(0.2),
    keras.layers.Dense(128),
    LeakyReLU(alpha=0.1),
    keras.layers.Dropout(0.1),
    keras.layers.Dense(10, activation='softmax')
])

# Compile model
model2.compile(optimizer='adam', loss='categorical_crossentropy',␣
 ↪metrics=['accuracy'])

# Print model summary
model2.summary()
```

```
Model: "sequential_30"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_42 (Conv2D)          (None, 98, 68, 64)        1792

 leaky_re_lu_7 (LeakyReLU)   (None, 98, 68, 64)        0

 max_pooling2d_42 (MaxPoolin  (None, 49, 34, 64)       0
 g2D)

 flatten_31 (Flatten)        (None, 106624)            0

 dense_76 (Dense)            (None, 216)               23031000

 leaky_re_lu_8 (LeakyReLU)   (None, 216)               0

 dropout_46 (Dropout)        (None, 216)               0

 dense_77 (Dense)            (None, 128)               27776

 leaky_re_lu_9 (LeakyReLU)   (None, 128)               0

 dropout_47 (Dropout)        (None, 128)               0

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_42 (Conv2D)          (None, 98, 68, 64)        1792
```

```
 leaky_re_lu_7 (LeakyReLU)   (None, 98, 68, 64)        0

 max_pooling2d_42 (MaxPoolin  (None, 49, 34, 64)       0
 g2D)

 flatten_31 (Flatten)        (None, 106624)            0

 dense_76 (Dense)            (None, 216)               23031000

 leaky_re_lu_8 (LeakyReLU)   (None, 216)               0

 dropout_46 (Dropout)        (None, 216)               0

 dense_77 (Dense)            (None, 128)               27776

 leaky_re_lu_9 (LeakyReLU)   (None, 128)               0

 dropout_47 (Dropout)        (None, 128)               0

 dense_78 (Dense)            (None, 10)                1290

=================================================================
Total params: 23,061,858
Trainable params: 23,061,858
Non-trainable params: 0
_________________________________________________________________
```

[ ]:
```python
history2 = model2.fit(X_train_reshaped, y_train_one_hot, epochs=20,␣
 ↪validation_data=(X_test_reshaped, y_test_one_hot))
```

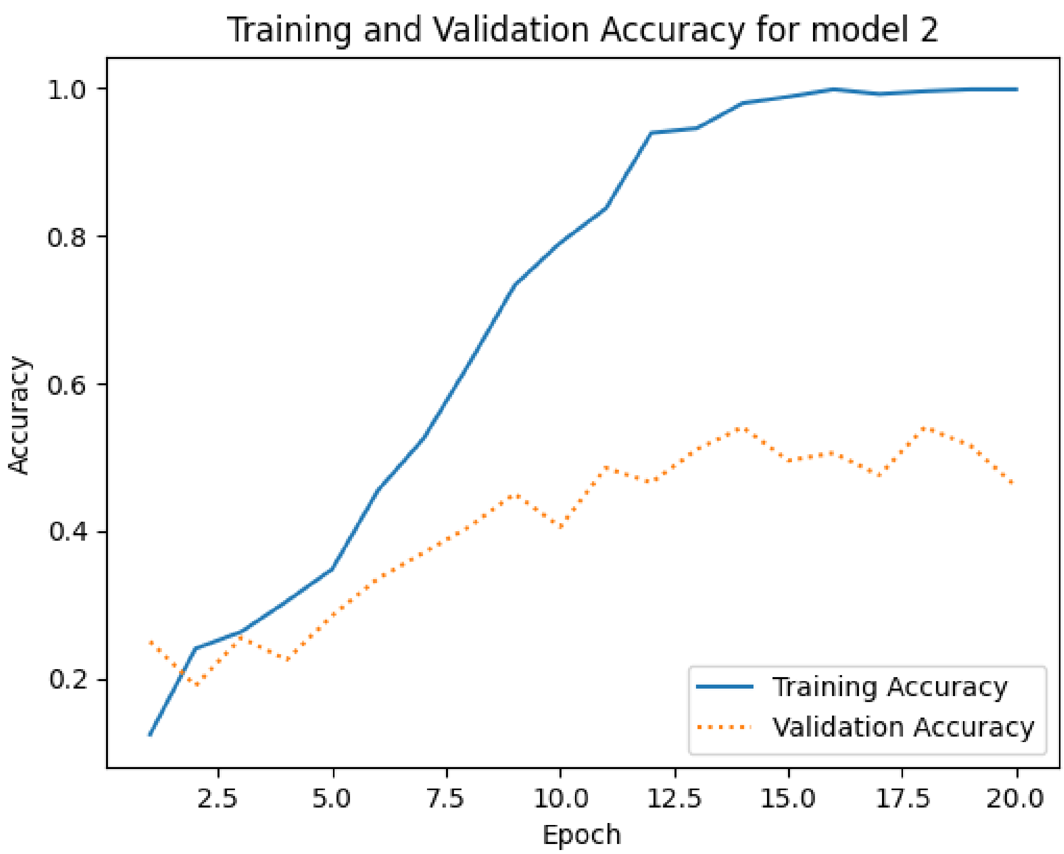
```
Epoch 1/20

2023-04-16 19:38:25.937693: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.

25/25 [==============================] - ETA: 0s - loss: 5.2792 - accuracy:
0.1239

2023-04-16 19:38:28.773806: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.

25/25 [==============================] - 3s 113ms/step - loss: 5.2792 -
accuracy: 0.1239 - val_loss: 2.1029 - val_accuracy: 0.2500
Epoch 2/20
Epoch 2/20
25/25 [==============================] - 2s 96ms/step - loss: 2.1115 - accuracy:
0.2403 - val_loss: 2.0683 - val_accuracy: 0.1900
```

```
Epoch 3/20
25/25 [==============================] - 2s 89ms/step - loss: 1.9993 - accuracy:
0.2628 - val_loss: 1.9821 - val_accuracy: 0.2550
Epoch 4/20
25/25 [==============================] - 2s 89ms/step - loss: 1.8890 - accuracy:
0.3041 - val_loss: 1.9971 - val_accuracy: 0.2250
Epoch 5/20
25/25 [==============================] - 2s 87ms/step - loss: 1.7691 - accuracy:
0.3479 - val_loss: 1.8451 - val_accuracy: 0.2850
Epoch 6/20
25/25 [==============================] - 2s 87ms/step - loss: 1.6079 - accuracy:
0.4543 - val_loss: 1.7730 - val_accuracy: 0.3350
Epoch 7/20
25/25 [==============================] - 2s 88ms/step - loss: 1.3617 - accuracy:
0.5244 - val_loss: 1.6710 - val_accuracy: 0.3700
Epoch 8/20
25/25 [==============================] - 2s 87ms/step - loss: 1.0907 - accuracy:
0.6258 - val_loss: 1.5692 - val_accuracy: 0.4050
Epoch 9/20
25/25 [==============================] - 2s 96ms/step - loss: 0.8184 - accuracy:
0.7322 - val_loss: 1.4696 - val_accuracy: 0.4500
Epoch 10/20
25/25 [==============================] - 2s 90ms/step - loss: 0.6414 - accuracy:
0.7897 - val_loss: 1.6548 - val_accuracy: 0.4050
Epoch 11/20
25/25 [==============================] - 2s 90ms/step - loss: 0.5033 - accuracy:
0.8360 - val_loss: 1.4528 - val_accuracy: 0.4850
Epoch 12/20
25/25 [==============================] - 2s 87ms/step - loss: 0.2672 - accuracy:
0.9387 - val_loss: 1.4447 - val_accuracy: 0.4650
Epoch 13/20
25/25 [==============================] - 2s 89ms/step - loss: 0.1924 - accuracy:
0.9449 - val_loss: 1.4954 - val_accuracy: 0.5100
Epoch 14/20
25/25 [==============================] - 2s 87ms/step - loss: 0.1153 - accuracy:
0.9787 - val_loss: 1.4490 - val_accuracy: 0.5400
Epoch 15/20
25/25 [==============================] - 2s 96ms/step - loss: 0.0741 - accuracy:
0.9875 - val_loss: 1.5289 - val_accuracy: 0.4950
Epoch 16/20
25/25 [==============================] - 2s 92ms/step - loss: 0.0448 - accuracy:
0.9975 - val_loss: 1.4922 - val_accuracy: 0.5050
Epoch 17/20
25/25 [==============================] - 2s 89ms/step - loss: 0.0477 - accuracy:
0.9912 - val_loss: 1.8398 - val_accuracy: 0.4750
Epoch 18/20
25/25 [==============================] - 2s 95ms/step - loss: 0.0356 - accuracy:
0.9950 - val_loss: 1.4675 - val_accuracy: 0.5400
```

```
Epoch 19/20
25/25 [==============================] - 2s 89ms/step - loss: 0.0250 - accuracy:
0.9975 - val_loss: 1.5995 - val_accuracy: 0.5150
Epoch 20/20
25/25 [==============================] - 2s 87ms/step - loss: 0.0175 - accuracy:
0.9975 - val_loss: 1.7582 - val_accuracy: 0.4600
```

[ ]:
```
acc = history2.history['accuracy']
val_acc = history2.history['val_accuracy']
epochs = range(1, len(acc) + 1)

plt.plot(epochs, acc, '-', label='Training Accuracy')
plt.plot(epochs, val_acc, ':', label='Validation Accuracy')
plt.title('Training and Validation Accuracy for model 2')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')
```

[ ]:
```
<matplotlib.legend.Legend at 0x2cdd466a0>
```



[ ]:
```
import tensorflow as tf

# Define the AlexNet model
def AlexNet(input_shape, num_classes):
    model = tf.keras.models.Sequential([
        # Convolutional layer 1
        tf.keras.layers.Conv2D(filters=96, kernel_size=(11,11), strides=(4,4),␣
↪padding='valid', activation='relu', input_shape=input_shape),
        tf.keras.layers.MaxPooling2D(pool_size=(3,3), strides=(2,2),␣
↪padding='valid'),
        tf.keras.layers.BatchNormalization(),

        # Convolutional layer 2
        tf.keras.layers.Conv2D(filters=256, kernel_size=(5,5), strides=(1,1),␣
↪padding='same', activation='relu'),
        tf.keras.layers.MaxPooling2D(pool_size=(3,3), strides=(2,2),␣
↪padding='valid'),
        tf.keras.layers.BatchNormalization(),

        # Convolutional layer 3
        tf.keras.layers.Conv2D(filters=384, kernel_size=(3,3), strides=(1,1),␣
↪padding='same', activation='relu'),
        tf.keras.layers.BatchNormalization(),

        # Convolutional layer 4
        tf.keras.layers.Conv2D(filters=384, kernel_size=(3,3), strides=(1,1),␣
↪padding='same', activation='relu'),
        tf.keras.layers.BatchNormalization(),

        # Convolutional layer 5
        tf.keras.layers.Conv2D(filters=256, kernel_size=(3,3), strides=(1,1),␣
↪padding='same', activation='relu'),
        tf.keras.layers.MaxPooling2D(pool_size=(3,3), strides=(2,2),␣
↪padding='valid'),
        tf.keras.layers.BatchNormalization(),

        # Flatten the output from the convolutional layers
        tf.keras.layers.Flatten(),

        # Fully connected layer 1
        tf.keras.layers.Dense(units=4096, activation='relu'),
        tf.keras.layers.Dropout(0.5),

        # Fully connected layer 2
        tf.keras.layers.Dense(units=4096, activation='relu'),
        tf.keras.layers.Dropout(0.5),
```

```python
        # Output layer
        tf.keras.layers.Dense(units=num_classes, activation='softmax')
    ])

    return model
model3 = AlexNet(input_shape, 10)
# Compile model
model3.compile(optimizer='adam', loss='categorical_crossentropy',␣
 ↪metrics=['accuracy'])

# Print model summary
model3.summary()
```

```
Model: "sequential_33"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_53 (Conv2D)          (None, 23, 15, 96)        34944

 max_pooling2d_49 (MaxPoolin  (None, 11, 7, 96)        0
 g2D)

 batch_normalization_21 (Bat  (None, 11, 7, 96)        384
 chNormalization)

 conv2d_54 (Conv2D)          (None, 11, 7, 256)        614656

 max_pooling2d_50 (MaxPoolin  (None, 5, 3, 256)        0
 g2D)

 batch_normalization_22 (Bat  (None, 5, 3, 256)        1024
 chNormalization)

 conv2d_55 (Conv2D)          (None, 5, 3, 384)         885120

 batch_normalization_23 (Bat  (None, 5, 3, 384)        1536
 chNormalization)

 conv2d_56 (Conv2D)          (None, 5, 3, 384)         1327488

 batch_normalization_24 (Bat  (None, 5, 3, 384)        1536
 chNormalization)

 conv2d_57 (Conv2D)          (None, 5, 3, 256)         884992

 max_pooling2d_51 (MaxPoolin  (None, 2, 1, 256)        0
 g2D)
```

```
 batch_normalization_25 (Bat  (None, 2, 1, 256)        1024
 chNormalization)

 flatten_34 (Flatten)        (None, 512)               0

 dense_85 (Dense)            (None, 4096)              2101248

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_53 (Conv2D)          (None, 23, 15, 96)        34944

 max_pooling2d_49 (MaxPoolin  (None, 11, 7, 96)        0
 g2D)

 batch_normalization_21 (Bat  (None, 11, 7, 96)        384
 chNormalization)

 conv2d_54 (Conv2D)          (None, 11, 7, 256)        614656

 max_pooling2d_50 (MaxPoolin  (None, 5, 3, 256)        0
 g2D)

 batch_normalization_22 (Bat  (None, 5, 3, 256)        1024
 chNormalization)

 conv2d_55 (Conv2D)          (None, 5, 3, 384)         885120

 batch_normalization_23 (Bat  (None, 5, 3, 384)        1536
 chNormalization)

 conv2d_56 (Conv2D)          (None, 5, 3, 384)         1327488

 batch_normalization_24 (Bat  (None, 5, 3, 384)        1536
 chNormalization)

 conv2d_57 (Conv2D)          (None, 5, 3, 256)         884992

 max_pooling2d_51 (MaxPoolin  (None, 2, 1, 256)        0
 g2D)

 batch_normalization_25 (Bat  (None, 2, 1, 256)        1024
 chNormalization)

 flatten_34 (Flatten)        (None, 512)               0

 dense_85 (Dense)            (None, 4096)              2101248
```

```
 dropout_52 (Dropout)        (None, 4096)             0

 dense_86 (Dense)            (None, 4096)             16781312

 dropout_53 (Dropout)        (None, 4096)             0

 dense_87 (Dense)            (None, 10)               40970

=================================================================
Total params: 22,676,234
Trainable params: 22,673,482
Non-trainable params: 2,752
_________________________________________________________________
```

[ ]:
```
history3 = model3.fit(X_train_reshaped, y_train_one_hot, epochs=20,␣
↪validation_data=(X_test_reshaped, y_test_one_hot))
```

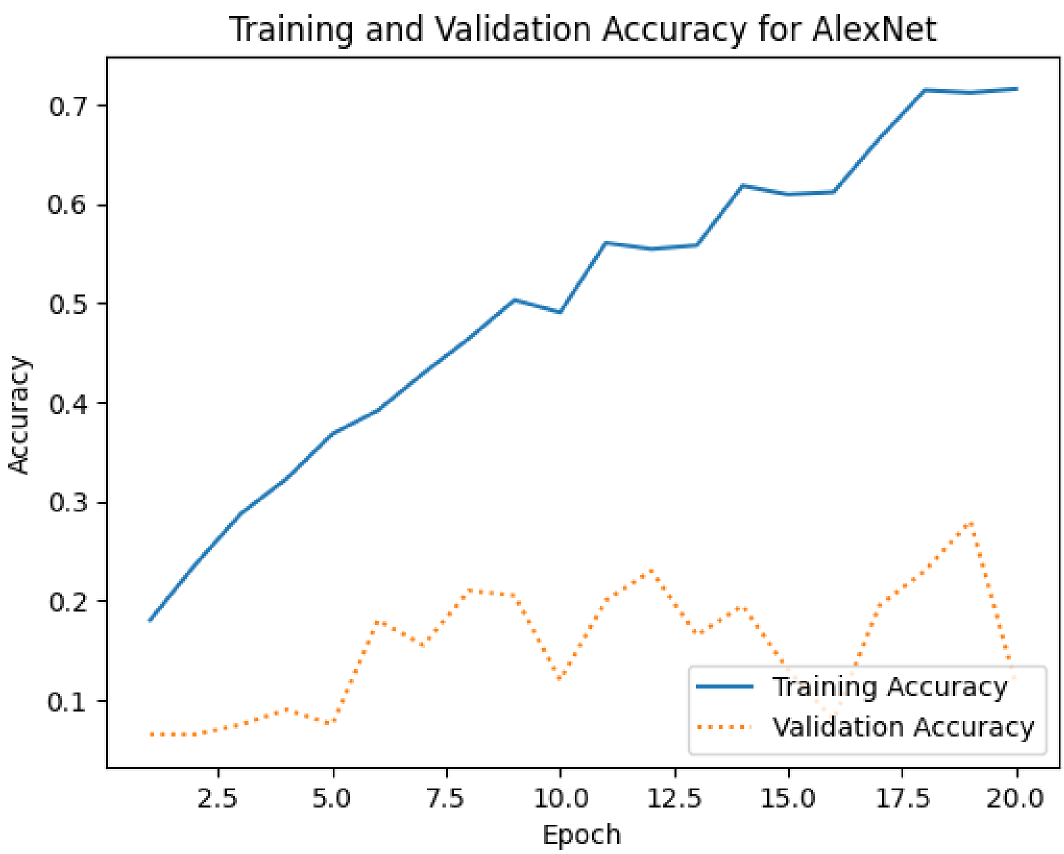
```
Epoch 1/20

2023-04-16 19:39:37.282980: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.

25/25 [==============================] - ETA: 0s - loss: 3.0315 - accuracy:
0.1802

2023-04-16 19:39:43.096270: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.

25/25 [==============================] - 7s 146ms/step - loss: 3.0315 -
accuracy: 0.1802 - val_loss: 5.9092 - val_accuracy: 0.0650
Epoch 2/20
Epoch 2/20
25/25 [==============================] - 2s 68ms/step - loss: 2.1320 - accuracy:
0.2365 - val_loss: 4.2810 - val_accuracy: 0.0650
Epoch 3/20
25/25 [==============================] - 2s 68ms/step - loss: 1.9450 - accuracy:
0.2879 - val_loss: 4.4332 - val_accuracy: 0.0750
Epoch 4/20
25/25 [==============================] - 2s 64ms/step - loss: 1.8114 - accuracy:
0.3229 - val_loss: 4.7994 - val_accuracy: 0.0900
Epoch 5/20
25/25 [==============================] - 2s 62ms/step - loss: 1.7209 - accuracy:
0.3680 - val_loss: 10.2604 - val_accuracy: 0.0750
Epoch 6/20
25/25 [==============================] - 2s 67ms/step - loss: 1.6505 - accuracy:
0.3917 - val_loss: 6.0424 - val_accuracy: 0.1800
Epoch 7/20
```

```
25/25 [==============================] - 2s 64ms/step - loss: 1.5404 - accuracy:
0.4293 - val_loss: 5.5076 - val_accuracy: 0.1550
Epoch 8/20
25/25 [==============================] - 1s 60ms/step - loss: 1.4855 - accuracy:
0.4643 - val_loss: 5.5863 - val_accuracy: 0.2100
Epoch 9/20
25/25 [==============================] - 2s 62ms/step - loss: 1.3332 - accuracy:
0.5031 - val_loss: 4.2907 - val_accuracy: 0.2050
Epoch 10/20
25/25 [==============================] - 1s 60ms/step - loss: 1.3956 - accuracy:
0.4906 - val_loss: 11.5004 - val_accuracy: 0.1200
Epoch 11/20
25/25 [==============================] - 2s 60ms/step - loss: 1.2097 - accuracy:
0.5607 - val_loss: 4.7443 - val_accuracy: 0.2000
Epoch 12/20
25/25 [==============================] - 2s 61ms/step - loss: 1.2549 - accuracy:
0.5544 - val_loss: 6.8092 - val_accuracy: 0.2300
Epoch 13/20
25/25 [==============================] - 2s 61ms/step - loss: 1.1238 - accuracy:
0.5582 - val_loss: 17.0100 - val_accuracy: 0.1650
Epoch 14/20
25/25 [==============================] - 2s 60ms/step - loss: 1.0561 - accuracy:
0.6183 - val_loss: 12.6391 - val_accuracy: 0.1950
Epoch 15/20
25/25 [==============================] - 2s 61ms/step - loss: 1.0557 - accuracy:
0.6095 - val_loss: 20.1991 - val_accuracy: 0.1300
Epoch 16/20
25/25 [==============================] - 2s 61ms/step - loss: 1.1104 - accuracy:
0.6120 - val_loss: 20.2748 - val_accuracy: 0.0800
Epoch 17/20
25/25 [==============================] - 2s 61ms/step - loss: 0.9231 - accuracy:
0.6658 - val_loss: 7.3416 - val_accuracy: 0.1950
Epoch 18/20
25/25 [==============================] - 2s 65ms/step - loss: 0.7418 - accuracy:
0.7146 - val_loss: 10.3693 - val_accuracy: 0.2300
Epoch 19/20
25/25 [==============================] - 2s 64ms/step - loss: 0.8063 - accuracy:
0.7121 - val_loss: 8.4882 - val_accuracy: 0.2800
Epoch 20/20
25/25 [==============================] - 2s 61ms/step - loss: 0.7494 - accuracy:
0.7159 - val_loss: 21.3820 - val_accuracy: 0.1150
```

[ ]:
```
acc = history3.history['accuracy']
val_acc = history3.history['val_accuracy']
epochs = range(1, len(acc) + 1)

plt.plot(epochs, acc, '-', label='Training Accuracy')
```

```python
plt.plot(epochs, val_acc, ':', label='Validation Accuracy')
plt.title('Training and Validation Accuracy for AlexNet')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')
```

```
[ ]: <matplotlib.legend.Legend at 0x2c8c443d0>
```



From the training, we can see that the accuracy for different models: - Logistic regression: 0.47 - SVC: 0.41 - MLP: doesn't run - CNN model1: 0.47 - CNN model2: 0.505 - ALexNet: 0.28

We can conclude that CNN has the best performance for classifying through image data.

2 Conclusion

Comparing the accruacy between classifcation through feature data and classification through image data, we can see that feature data has better performance result. It might becuase feature data might be able to capture more meaningful and relevant information about the data compared to the raw image data. It might also be less noisy, or having lower dimensional compared to raw image data, which can make it easier for the model to learn a decision boundary between classes. From the modeling result, we can see that image data can have very high dimensionality, which can lead to overfitting or difficulty in training.

Reference: - Work w/ Audio Data: Visualise, Classify, Recommend - Audio classification using convolutional neural networks - github: multilayer_perceptron