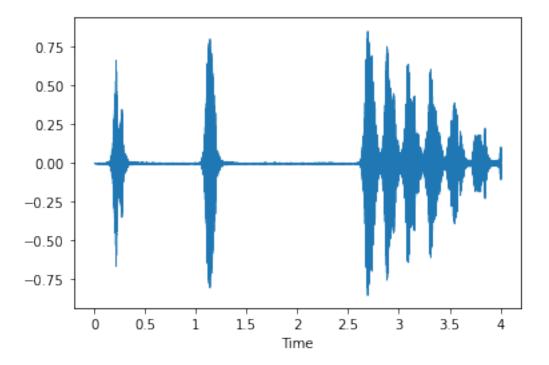
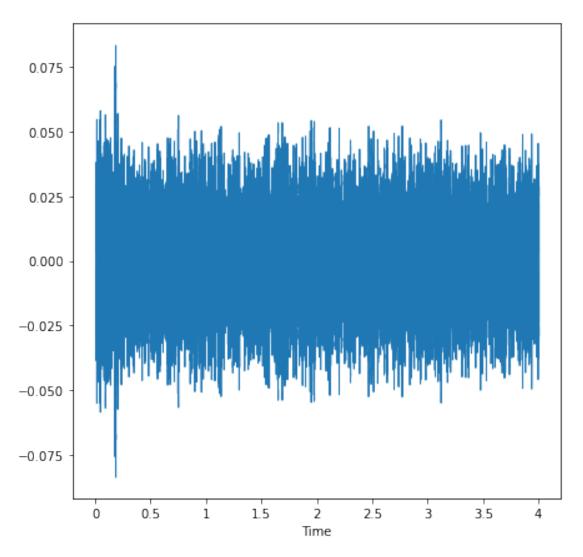
#Showing our first wave of the audio data
librosa.display.waveshow(data,sr=sample_rate)
ipd.Audio(filename) #Audio clip of the first audio data

<IPython.lib.display.Audio object>



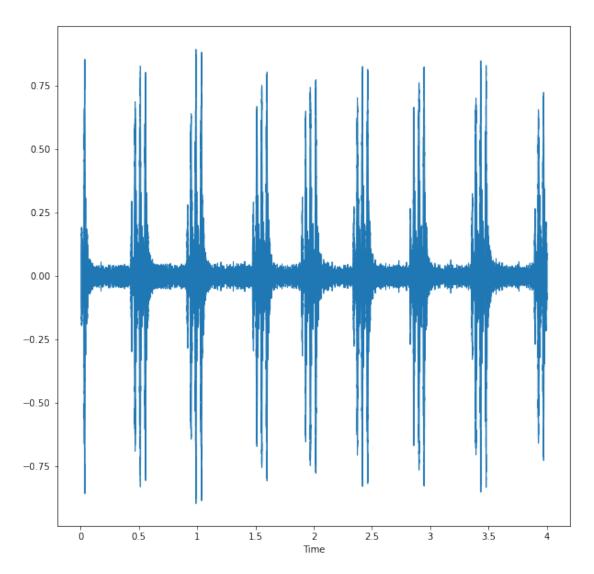
#Same as previous but audio data is different
file='urban/fold9/103249-5-0-10.wav'
plt.figure(figsize=(7,7))
data,sample_rate=librosa.load(file)
librosa.display.waveshow(data,sr=sample_rate)
ipd.Audio(file)

<IPython.lib.display.Audio object>



#Same as previous
file='urban/fold9/101729-0-0-24.wav'
plt.figure(figsize=(10,10))
data,sample_rate=librosa.load(file)
librosa.display.waveshow(data,sr=sample_rate)
ipd.Audio(file)

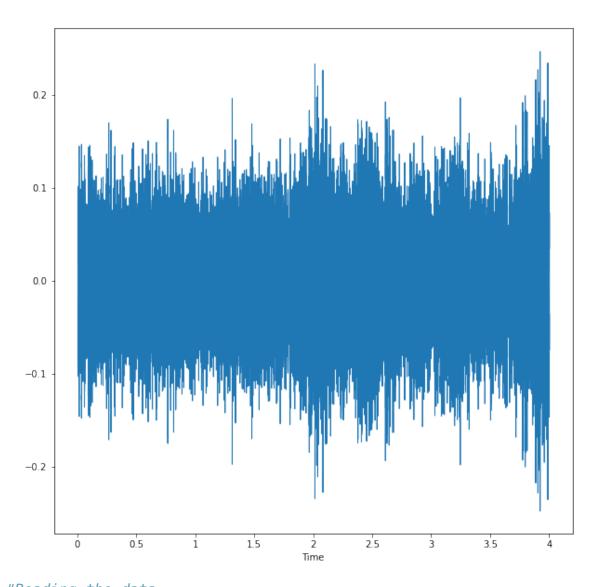
<IPython.lib.display.Audio object>



#Same

```
file='urban/fold4/115415-9-0-7.wav'
plt.figure(figsize=(10,10))
data,sample_rate=librosa.load(file)
librosa.display.waveshow(data,sr=sample_rate)
ipd.Audio(file)
```

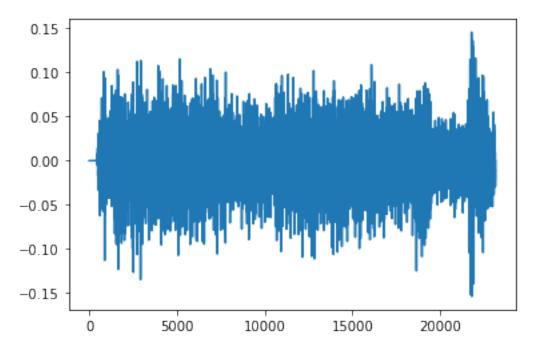
<IPython.lib.display.Audio object>



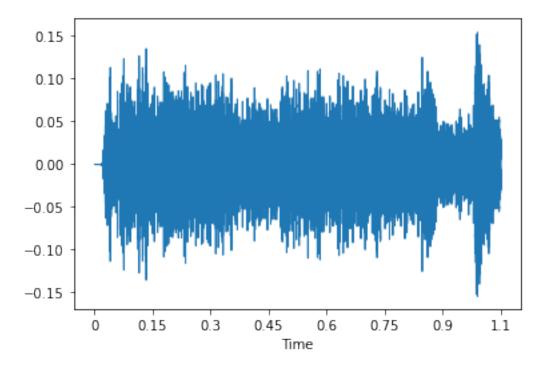
#Reading the data
import pandas as pd
metadata=pd.read_csv('urban/UrbanSound8K.csv')
metadata.head()

c 1	slice_file_name assID \	fsID	start	end	salience	fold
0	100032-3-0-0.wav	100032	0.0	0.317551	1	5
1	100263-2-0-117.wav	100263	58.5	62.500000	1	5
2	100263-2-0-121.wav	100263	60.5	64.500000	1	5
3	100263-2-0-126.wav	100263	63.0	67.000000	1	5
4	100263-2-0-137.wav	100263	68.5	72.500000	1	5

```
class
           dog_bark
0
  children_playing
1
2
  children_playing
3
   children_playing
  children_playing
metadata['class'].value_counts()
dog bark
                    1000
children playing
                    1000
air conditioner
                    1000
street_music
                    1000
engine_idling
                    1000
jackhammer
                    1000
drilling
                    1000
                     929
siren
car horn
                     429
                     374
gun shot
Name: class, dtype: int64
file='urban/fold10/100648-1-1-0.wav'
data,sample_rate=librosa.load(file)
print(data)
[ 0.
              0.
                          0.
                                      ... -0.02467388 -0.01529006
  0.
plt.plot(data)
[<matplotlib.lines.Line2D at 0x2c2e907e190>]
```



librosa.display.waveshow(data,sr=sample_rate)
librosa.display.AdaptiveWaveplot at 0x2c2e90e0100>



ipd.Audio(file)
<IPython.lib.display.Audio object>

#Mfccs- mel-frequency crapstral coefficients mfccs=librosa.feature.mfcc(y=data,sr=sample rate) mfccs array([[-3.81742462e+02, -2.39318420e+02, -2.00840012e+02, -1.97661453e+02, -1.90769394e+02, -1.82279953e+02,

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```

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```

```
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                                            2.51292276e+00,
        -3.14756966e+00, 1.71539664e+00,
                                            6.44806862e+00,
         6.14509583e+00]], dtype=float32)
mfccs.shape
(20, 46)
#Calculating mfcc for the audio data named as file
file='urban/fold8/103076-3-0-0.wav'
data,sample rate=librosa.load(file)
mfccs2=librosa.feature.mfcc(y=data,sr=sample rate)
mfccs2
                                                  , ..., -481.6944
array([[-515.92267
                      -484.46594
                                    -398.35062
                       -490.18924
        -485.69058
                                   ],
          18.905098
                        56.696026 ,
                                      125.05409
                                                           50.337784 ,
          46.759377
                        43.654747 ],
          10.733795 ,
                        32.066864
                                       17.022207 , ...,
                                                            7.900363 ,
           7.6215253,
                        10.265154 ],
           6.400581 ,
                                        9.1847725, ...,
                          4.0845275,
                                                         -11.392929 ,
         -12.2220335,
                        -13.293634 ],
                                        5.451171 , ...,
           6.088352 ,
                          1.1501071,
                                                           -9.292716 ,
          -9.7056
                        -10.057598],
                                       -9.950499 , ...,
           3.3120189,
                        -1.4564419,
                                                           -5.2907166,
          -4.2817717,
                        -5.1364794]], dtype=float32)
mfccs2.shape
```

```
(20, 109)
audio data path='urban'
#Calulating mfcc for all the audio data
def features extractor(file):
    audio data, sample rate = librosa.load(file name,
res type= kaiser fast')
    mfccs features = librosa.feature.mfcc(y=audio data,
sr=sample rate, n mfcc=40)
    mfccs scaled features = np.mean(mfccs features.T,axis=0)
    return mfccs scaled features
import numpy as np
from tqdm import tqdm
import os as o
extracted features=[]
for index num,row in tqdm(metadata.iterrows()):
file name=o.path.join(o.path.abspath(audio data path), 'fold'+str(row['
fold'])+'/',str(row['slice file name']))
    final class labels=row['class']
    data=features extractor(file name)
    extracted features.append([data,final class labels])
3555it [03:02, 19.71it/s]C:\Users\VICKY R R\anaconda3\lib\site-
packages\librosa\util\decorators.py:88: UserWarning: n fft=2048 is too
small for input signal of length=1323
  return f(*args, **kwargs)
8324it [06:35, 20.76it/s]C:\Users\VICKY R R\anaconda3\lib\site-
packages\librosa\util\decorators.py:88: UserWarning: n fft=2048 is too
small for input signal of length=1103
  return f(*args, **kwargs)
8329it [06:36, 26.60it/s]C:\Users\VICKY R R\anaconda3\lib\site-
packages\librosa\util\decorators.py:88: UserWarning: n fft=2048 is too
small for input signal of length=1523
  return f(*args, **kwargs)
8732it [06:52, 21.17it/s]
#Converting extracted features into a dataframe
df=pd.DataFrame(extracted features, columns=['features', 'class'])
df.head()
                                            features
                                                                  class
   [-217.35526, 70.22338, -130.38527, -53.282898, \ldots]
                                                               dog bark
  [-424.09818, 109.34077, -52.919525, 60.86475, ...
                                                     children playing
  [-458.79114, 121.38419, -46.520657, 52.00812, ... children playing
  [-413.89984, 101.66373, -35.42945, 53.036354, ...
                                                      children playing
  [-446.60352, 113.68541, -52.402206, 60.302044,... children playing
```

```
df.shape
(8732, 2)
#Dividing the data into train and test
x=np.array(df['features'].tolist())
y=np.array(df['class'].tolist())
Х
array([[-2.1735526e+02,
                        7.0223381e+01, -1.3038527e+02, ...,
       -1.6930529e+00, -6.1698371e-01, 3.8600543e-01],
                       1.0934077e+02, -5.2919525e+01, ...,
       [-4.2409818e+02,
        5.3489321e-01, -5.4468727e-01, 4.4632098e-01],
       [-4.5879114e+02, 1.2138419e+02, -4.6520657e+01, ...,
        2.0768483e+00,
                        1.6962963e+00, -9.6140963e-01],
       [-3.0388824e+02, 1.1135945e+02, -4.5941563e+01, ...,
       -3.0292380e+00, 2.7170298e+00, 7.6197419e+00],
       [-3.4411008e+02,
                        1.2545021e+02, -5.4903442e+01, ...,
       -7.9082441e+00, -1.6414586e+00, 5.6668439e+00],
       [-3.1560281e+02, 9.4854805e+01, -3.7222340e+01, ...,
        6.1386460e-01, -1.1449189e+01, -6.0105853e+00]],
dtype=float32)
У
x.shape
(8732, 40)
y.shape
(8732,)
print(x.mean(),x.std())
-3.4118054 47.55431
#Applying label encoding to y
from tensorflow.keras.utils import to categorical
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
y=to categorical(le.fit transform(y))
array([[0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 1., \ldots, 0., 0., 0.]
       [0., 0., 1., \ldots, 0., 0., 0.]
       . . . ,
```

```
[0., 1., 0., \ldots, 0., 0., 0.]
       [0., 1., 0., \ldots, 0., 0., 0.]
       [0., 1., 0., ..., 0., 0., 0.]], dtype=float32)
from sklearn.model selection import train test split
x train,x test,y train,y test=train test split(x,y,test size=0.30)
print(x train.shape,x test.shape,y train.shape,y test.shape)
(6112, 40) (2620, 40) (6112, 10) (2620, 10)
x train
array([[-5.39083801e+02,
                          1.18879990e+02, -2.12978706e+01, ...,
         1.43910885e+00,
                          4.27504629e-01,
                                            1.14806557e+00],
       [-3.85882782e+02,
                          1.58166977e+02, -2.13433208e+01, ...,
         6.21687412e-01, -1.46509886e+00, -3.36106420e+00],
                          5.16823692e+01, -5.42805367e+01, ...,
       [-2.97461426e+02.
         1.67091846e+00, -1.75430465e+00, 2.84418732e-01],
                          1.07195564e+02, -6.84187775e+01, ...,
       [-2.46721054e+02,
         2.54747778e-01,
                          4.84547287e-01, -4.68080938e-01],
                          1.05620338e+02, -1.92326412e+01, ...,
       [-2.19870026e+02,
                          1.96077079e-01, 3.28308463e+00],
         1.99260962e+00,
       [-4.74945221e+02,
                          6.03058968e+01, -1.67592487e+01, ...,
         2.02000237e+00,
                          1.62229729e+00, 3.82520765e-01]],
dtype=float32)
x train.shape
(6112, 40)
x test.shape
(2620, 40)
y train.shape
(6112, 10)
from tensorflow.keras import layers, models
#Building the model
nn=models.Sequential([
    layers.Dense(99,input shape=(40,),activation='relu'),
    layers.Dense(34,activation='relu'),
    layers.Dense(10,activation='softmax')
```

nn.summary()

Model: "sequential"

Layer (type)	Output	Shape	Param #						
dense (Dense)	(None,	99)	4059						
dense_1 (Dense)	(None,	34)	3400						
dense_2 (Dense)	(None,	10)	350						
Total params: 7,809 Trainable params: 7,809 Non-trainable params: 0									
#Fitting the model with x_train and y_train									
<pre>nn.compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accuracy']) from tensorflow.keras.callbacks import ModelCheckpoint from datetime import datetime</pre>									
<pre>num_epochs = 25 num_batch_size = 32</pre>									
<pre>checkpointer = ModelCheckpoint(filepath='saved_models/audio_classification.hdf5',</pre>									
<pre>nn.fit(x_train, y_train, batch_size=num_batch_size, epochs=num_epochs, validation_data=(x_test, y_test), callbacks=[checkpointer], verbose=1)</pre>									
<pre>duration = datetime.now() - start print("Training completed in time: ", duration)</pre>									
Epoch 1/25 178/191 [===================================	rom inf cation.h ====== ss: 1.50	to 1.50950, saving df5 ====] - 1s 2ms/step 95 - val_accuracy:	model to - loss: 4.4245 0.5122						

```
Epoch 2: val loss improved from 1.50950 to 1.31360, saving model to
saved models\audio classification.hdf5
- accuracy: 0.5146 - val loss: 1.3136 - val accuracy: 0.5779
Epoch 3/25
accuracy: 0.5911
Epoch 3: val loss improved from 1.31360 to 1.21986, saving model to
saved models\audio classification.hdf5
- accuracy: 0.5924 - val loss: 1.2199 - val accuracy: 0.5977
Epoch 4/25
accuracy: 0.6357
Epoch 4: val loss improved from 1.21986 to 1.02237, saving model to
saved models\audio classification.hdf5
- accuracy: 0.6392 - val_loss: 1.0224 - val_accuracy: 0.6786
Epoch 5/25
accuracy: 0.6587
Epoch 5: val loss did not improve from 1.02237
- accuracy: 0.6595 - val loss: 1.0680 - val accuracy: 0.6469
Epoch 6/25
accuracy: 0.6857
Epoch 6: val loss improved from 1.02237 to 0.98835, saving model to
saved models\audio classification.hdf5
- accuracy: 0.6857 - val loss: 0.9884 - val accuracy: 0.6756
Epoch 7/25
157/191 [============>.....] - ETA: 0s - loss: 0.9184 -
accuracy: 0.7122
Epoch 7: val loss did not improve from 0.98835
- accuracy: 0.7140 - val loss: 1.0136 - val accuracy: 0.6718
Epoch 8/25
accuracy: 0.7023
Epoch 8: val loss improved from 0.98835 to 0.89379, saving model to
saved models\audio classification.hdf5
- accuracy: 0.7088 - val loss: 0.8938 - val accuracy: 0.7130
Epoch 9/25
accuracy: 0.7356
Epoch 9: val loss improved from 0.89379 to 0.84424, saving model to
saved models\audio classification.hdf5
```

```
- accuracy: 0.7382 - val loss: 0.8442 - val accuracy: 0.7244
Epoch 10/25
133/191 [==========>.....] - ETA: 0s - loss: 0.8080 -
accuracy: 0.7399
Epoch 10: val_loss did not improve from 0.84424
- accuracy: 0.7333 - val loss: 1.0630 - val accuracy: 0.6710
Epoch 11/25
120/191 [==========>.....] - ETA: 0s - loss: 0.7692 -
accuracy: 0.7492
Epoch 11: val loss did not improve from 0.84424
- accuracy: 0.7462 - val loss: 0.8856 - val accuracy: 0.7137
Epoch 12/25
accuracy: 0.7629
Epoch 12: val loss improved from 0.84424 to 0.77745, saving model to
saved_models\audio_classification.hdf5
- accuracy: 0.7598 - val loss: 0.7775 - val accuracy: 0.7538
Epoch 13/25
accuracy: 0.7753
Epoch 13: val loss did not improve from 0.77745
- accuracy: 0.7768 - val loss: 0.8056 - val accuracy: 0.7492
Epoch 14/25
accuracy: 0.7723
Epoch 14: val loss improved from 0.77745 to 0.75681, saving model to
saved models\audio classification.hdf5
- accuracy: 0.7755 - val loss: 0.7568 - val accuracy: 0.7565
Epoch 15/25
accuracy: 0.7869
Epoch 15: val loss improved from 0.75681 to 0.71018, saving model to
saved models\audio classification.hdf5
- accuracy: 0.7889 - val loss: 0.7102 - val accuracy: 0.7805
Epoch 16/25
accuracy: 0.8029
Epoch 16: val loss improved from 0.71018 to 0.69568, saving model to
saved models\audio classification.hdf5
- accuracy: 0.8032 - val loss: 0.6957 - val_accuracy: 0.7794
Epoch 17/25
accuracy: 0.7994
```

```
Epoch 17: val loss did not improve from 0.69568
- accuracy: 0.7999 - val loss: 0.7174 - val accuracy: 0.7813
Epoch 18/25
accuracy: 0.7969
Epoch 18: val loss improved from 0.69568 to 0.65698, saving model to
saved models\audio classification.hdf5
- accuracy: 0.7997 - val loss: 0.6570 - val accuracy: 0.7985
Epoch 19/25
127/191 [===========>.....] - ETA: 0s - loss: 0.5375 -
accuracy: 0.8238
Epoch 19: val loss did not improve from 0.65698
- accuracy: 0.8204 - val loss: 0.7288 - val accuracy: 0.7683
Epoch 20/25
135/191 [===========>.....] - ETA: 0s - loss: 0.5313 -
accuracy: 0.8315
Epoch 20: val loss did not improve from 0.65698
- accuracy: 0.8258 - val loss: 0.6849 - val accuracy: 0.7798
Epoch 21/25
accuracy: 0.8272
Epoch 21: val loss did not improve from 0.65698
- accuracy: 0.8272 - val loss: 0.7329 - val_accuracy: 0.7870
Epoch 22/25
accuracy: 0.8270
Epoch 22: val_loss did not improve from 0.65698
- accuracy: 0.8276 - val loss: 0.6730 - val accuracy: 0.7981
Epoch 23/25
accuracy: 0.8319
Epoch 23: val loss did not improve from 0.65698
- accuracy: 0.8341 - val loss: 0.6930 - val accuracy: 0.7866
Epoch 24/25
accuracy: 0.8403
Epoch 24: val loss improved from 0.65698 to 0.64015, saving model to
saved models\audio classification.hdf5
- accuracy: 0.8424 - val loss: 0.6402 - val accuracy: 0.8004
Epoch 25/25
accuracy: 0.8408
```

```
Epoch 25: val loss did not improve from 0.64015
- accuracy: 0.8403 - val_loss: 0.6610 - val_accuracy: 0.7939
Training completed in time: 0:00:07.994652
#Evaluating the model
nn.evaluate(x test,y test)
- accuracy: 0.7939
[0.660993754863739, 0.7938931584358215]
x test[0]
array([-3.07885376e+02, 1.16959885e+02, -2.37968731e+01,
5.06708374e+01,
      -1.15026798e+01, 1.17254210e+01, -2.68075600e+01, -
9.66017151e+00,
      -1.40686779e+01, 6.13431406e+00, -8.52104664e+00,
1.02833481e+01,
      -5.67926121e+00, 7.07702637e+00, -6.68003035e+00,
7.21004486e+00,
      -6.55538797e+00, 2.18808293e+00, -2.09531426e+00,
4.31734419e+00,
      -4.68917656e+00, 7.10129881e+00, 2.22657728e+00,
2.93233061e+00,
      -4.17351198e+00, 1.72676504e+00, -1.79248297e+00, -
1.06432699e-01,
      -1.91668153e+00, 1.12393749e+00, -1.21858978e+00, -
1.49600852e+00,
       6.49398804e-01, 1.18790329e+00, -1.59171557e+00, -
1.67435384e+00,
      -1.11851943e+00, -1.62678170e+00, -1.92182100e+00, -
1.76350689e+00],
     dtvpe=float32)
filename="../input/urbansound8k/fold1/101415-3-0-2.wav"
prediction feature=features extractor(filename)
prediction feature=prediction feature.reshape(1,-1)
y pred=nn.predict(prediction feature)
y_pred
1/1 [======= ] - 0s 78ms/step
array([[2.35994172e-04, 8.91029119e-01, 2.74627632e-03, 1.03534214e-
04,
       2.42649317e-02, 1.70655048e-03, 1.25769677e-03, 1.56417227e-
05,
       3.82983498e-03, 7.48103932e-02]], dtype=float32)
np.argmax(y pred,axis=1)
```

```
array([1], dtype=int64)
#Testing with some random audio data
filename="urban/fold10/101382-2-0-20.wav"
audio, sample rate = librosa.load(filename, res type='kaiser fast')
mfccs features = librosa.feature.mfcc(y=audio, sr=sample rate,
n mfcc=40)
mfccs scaled features = np.mean(mfccs features.T,axis=0)
print(mfccs scaled features)
mfccs scaled features=mfccs scaled features.reshape(1,-1)
print(mfccs scaled features)
print(mfccs scaled features.shape)
predicted label=nn.predict(mfccs scaled features)
predicted label=np.argmax(predicted label,axis=1)
print(predicted_label)
prediction class = le.inverse transform(predicted label)
prediction class
[-2.9286816e+02 7.6148514e+01 -8.9283424e+01 -1.7439636e+01
 -3.5680817e+01 -2.1628220e+01 -2.3610415e+01 -1.7398737e+01
 -1.9349104e+01 -2.0335127e+01 -1.8246513e+01 6.0138435e+00
 -1.1755315e+01 4.6790963e-01 -5.9090028e+00 -1.2833057e-01
 -7.0852609e+00 8.7631667e-01 -5.6806302e+00 -6.3838940e+00
 -7.8490171e+00 -5.1395953e-01 -2.5704169e+00 -8.5713613e-01
 -3.8996730e+00 -1.2656254e+00 -4.9632006e+00 -3.8195801e+00
  2.9782119e+00 -1.1003333e+00 4.5313558e-01 4.1021395e+00
  2.5452676e+00 2.0834954e+00 1.1725211e+00 3.1504326e+00
  2.4951210e+00 1.8432283e+00 1.5362173e+00 -6.5870523e-01]
[-2.9286816e+02 \quad 7.6148514e+01 \quad -8.9283424e+01 \quad -1.7439636e+01
  -3.5680817e+01 -2.1628220e+01 -2.3610415e+01 -1.7398737e+01
  -1.9349104e+01 -2.0335127e+01 -1.8246513e+01 6.0138435e+00
  -1.1755315e+01 4.6790963e-01 -5.9090028e+00 -1.2833057e-01
  -7.0852609e+00 8.7631667e-01 -5.6806302e+00 -6.3838940e+00
  -7.8490171e+00 -5.1395953e-01 -2.5704169e+00 -8.5713613e-01
  -3.8996730e+00 -1.2656254e+00 -4.9632006e+00 -3.8195801e+00
   2.9782119e+00 -1.1003333e+00  4.5313558e-01  4.1021395e+00
   2.5452676e+00 2.0834954e+00 1.1725211e+00 3.1504326e+00
   2.4951210e+00 1.8432283e+00 1.5362173e+00 -6.5870523e-01]]
(1, 40)
1/1 [======= ] - 0s 16ms/step
[2]
array(['children playing'], dtype='<U16')</pre>
ipd.Audio(filename)
<IPython.lib.display.Audio object>
#Testing with some audio data
x='urban/fold10/100648-1-0-0.wav'
```

```
audio, sample rate = librosa.load(x, res type='kaiser fast')
mfccs features = librosa.feature.mfcc(y=audio, sr=sample rate,
n mfcc=40)
mfccs scaled features = np.mean(mfccs features.T,axis=0)
print(mfccs scaled features)
mfccs scaled features=mfccs scaled features.reshape(1,-1)
print(mfccs scaled features)
print(mfccs scaled features.shape)
predicted label=nn.predict(mfccs scaled features)
predicted label=np.argmax(predicted label,axis=1)
print(predicted label)
prediction class = le.inverse transform(predicted label)
prediction class
[-196.822]
                113.993126
                              -13.813408
                                              0.4022098
                                                           -20.145586
   -4.7625513
                -40.68413
                                4.171539
                                            -18.973984
                                                           -3.0413852
  -19.736597
                  7.505515
                              -21.69197
                                             -4.053084
                                                           -20.116354
    4.8145556
                -14.817319
                                0.9286656
                                            -14.061541
                                                            8.725959
   -6.6515527
                  6.45562
                                              0.5490027
                                                           -9.6971445
                               -4.6819024
   -0.34578848
                 -8.687981
                               -0.67337924
                                             -6.8771744
                                                            5.059755
                                              4.441565
                                                           -7.439074
  -10.099091
                 -0.25963083
                               -2.8073726
   -4.4811225
                 -1.9385126
                                3.842505
                                             -5.9479365
0.9880176 1
[[-196.822
                 113.993126
                               -13.813408
                                               0.4022098
                                                           -20.145586
    -4.7625513
                 -40.68413
                                 4.171539
                                             -18.973984
                                                            -3.0413852
   -19.736597
                   7.505515
                               -21.69197
                                              -4.053084
                                                           -20.116354
     4.8145556
                 -14.817319
                                 0.9286656
                                             -14.061541
                                                             8.725959
                                               0.5490027
    -6.6515527
                   6.45562
                                -4.6819024
                                                            -9.6971445
    -0.34578848
                  -8.687981
                                -0.67337924
                                              -6.8771744
                                                             5.059755
   -10.099091
                  -0.25963083
                                -2.8073726
                                               4.441565
                                                            -7.439074
                                              -5.9479365
    -4.4811225
                  -1.9385126
                                 3.842505
                                                            -0.9880176
]]
(1, 40)
1/1 [======] - 0s 16ms/step
[4]
array(['drilling'], dtype='<U16')</pre>
ipd.Audio(x)
<IPython.lib.display.Audio object>
#Testing with random audio data
v='urban/fold10/100648-1-1-0.wav'
audio, sample_rate = librosa.load(y, res_type='kaiser_fast')
mfccs_features = librosa.feature.mfcc(y=audio, sr=sample_rate,
mfccs scaled features = np.mean(mfccs features.T,axis=0)
print(mfccs scaled features)
```

```
mfccs scaled features=mfccs scaled features.reshape(1,-1)
print(mfccs scaled features)
print(mfccs scaled features.shape)
predicted label=nn.predict(mfccs scaled features)
predicted label=np.argmax(predicted label,axis=1)
print(predicted label)
prediction class = le.inverse transform(predicted label)
prediction class
[-203.38026
               110.47649
                            -27.654587
                                          13.878089
                                                      -25.771694
               -24.84813
  -11.791375
                              3.826014
                                         -27.55837
                                                        9.07529
                                                       -13.73274
  -20.859709
                 5.4129763
                            -24.00172
                                           5.662438
   -3.0151746
                             -1.2490004
                                         -14.489137
               -14.304382
                                                        3.142862
  -11.586273
                 3.9236944
                             -8.836533
                                          -1.4830024
                                                       -6.2751427
   -1.2972062
                -8.606145
                              0.5964239
                                          -9.304495
                                                        3.5240953
    0.5034145
                -2.811972
                             -2.8778977
                                           5.0855837
                                                       -8.883842
   -5.634365
                 6.706231
                              2.3156214
                                         -13.47779
                                                        3.2116613]
[[-203.38026
                110.47649
                             -27.654587
                                           13.878089
                                                       -25.771694
   -11.791375
                -24.84813
                               3.826014
                                          -27.55837
                                                         9.07529
   -20.859709
                  5.4129763
                             -24.00172
                                            5.662438
                                                       -13.73274
    -3.0151746
                -14.304382
                              -1.2490004
                                          -14.489137
                                                         3.142862
   -11.586273
                  3.9236944
                              -8.836533
                                           -1.4830024
                                                        -6.2751427
    -1.2972062
                 -8.606145
                                           -9.304495
                               0.5964239
                                                         3.5240953
                              -2.8778977
     0.5034145
                 -2.811972
                                            5.0855837
                                                        -8.883842
    -5.634365
                  6.706231
                               2.3156214
                                          -13.47779
                                                         3.211661311
(1, 40)
1/1 [======= ] - 0s 16ms/step
[1]
array(['car horn'], dtype='<U16')
ipd.Audio(y)
<IPython.lib.display.Audio object>
v='urban/fold1/101415-3-0-2.wav'
audio, sample rate = librosa.load(v, res_type='kaiser_fast')
mfccs features = librosa.feature.mfcc(y=audio, sr=sample rate,
n mfcc=40)
mfccs scaled features = np.mean(mfccs features.T,axis=0)
print(mfccs scaled features)
mfccs scaled features=mfccs scaled features.reshape(1,-1)
print(mfccs scaled features)
print(mfccs scaled features.shape)
predicted label=nn.predict(mfccs scaled features)
predicted_label=np.argmax(predicted_label,axis=1)
print(predicted label)
prediction class = le.inverse transform(predicted label)
prediction class
```

```
1.7812963e+01 -1.1735518e+01
[-4.0345078e+02
               9.3772453e+01
 -7.2203588e+00
                3.7652965e+00 -1.6174644e+01 -6.8593187e+00
 -1.0542680e+01 -5.1888270e+00
                              4.1709691e-02 -4.9357162e+00
 9.3806309e-01
                1.2813916e+00
                              4.6511507e-01
                                             6.1276870e+00
                3.2279246e+00 -4.2884707e+00 -3.6228058e+00
 2.8408828e+00
 -1.8678902e+00 -3.1442461e+00 -3.5220675e+00 -5.6707931e+00
 -1.8247030e+00 -2.4657447e+00 -2.8244348e+00
                                             7.6615348e-02
 -5.8698922e-01 -1.0786054e-01 -8.9683491e-01 -1.0526063e+00
 -2.6228976e+00 -5.0490838e-01 -1.9731140e+00 -2.9963651e+00
 -3.0717986e+00 -1.4866264e+00 -2.4471817e+00 -2.8644500e+001
[[-4.0345078e+02
                 9.3772453e+01 1.7812963e+01 -1.1735518e+01
  -7.2203588e+00
                 3.7652965e+00 -1.6174644e+01 -6.8593187e+00
  -1.0542680e+01 -5.1888270e+00
                               4.1709691e-02 -4.9357162e+00
  9.3806309e-01
                 1.2813916e+00
                               4.6511507e-01
                                              6.1276870e+00
  2.8408828e+00
                 3.2279246e+00 -4.2884707e+00 -3.6228058e+00
  -1.8678902e+00 -3.1442461e+00 -3.5220675e+00 -5.6707931e+00
  -1.8247030e+00 -2.4657447e+00 -2.8244348e+00
                                              7.6615348e-02
  -5.8698922e-01 -1.0786054e-01 -8.9683491e-01 -1.0526063e+00
 -2.6228976e+00 -5.0490838e-01 -1.9731140e+00 -2.9963651e+00
  -3.0717986e+00 -1.4866264e+00 -2.4471817e+00 -2.8644500e+0011
(1, 40)
[3]
array(['dog bark'], dtype='<U16')
ipd.Audio(v)
<IPython.lib.display.Audio object>
```