Importing all necessary libraries

In [ ]:
```
from IPython.display import Audio, display
import IPython.display as ipd

import librosa
from librosa import display

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

import tensorflow as tf
from tensorflow.keras.callbacks import EarlyStopping

from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, accuracy_score
from sklearn.preprocessing import StandardScaler

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv1D, MaxPooling1D, Flatten, Dense
from tensorflow.keras.utils import to_categorical

from tensorflow.keras.models import load_model
```

Function for loading dataset

In [ ]:
```
def load_dataset(path):
    """Loads dataset from path provided and return pandas object"""
    ds_path= path
    ds= pd.read_csv(ds_path)
    return ds
```

Function for loading audios using librosa

In [ ]:
```
def audio_signals(path, sample_rate=16000, duration=3):
    """Loading audio using librosa library"""
    audio, sr= librosa.load(path, sr=sample_rate, duration=duration, mono=True)
    if sr!=sample_rate:
        audio = librosa.resample(audio, sr, sample_rate)
    return audio

def load_audio_signals(ds, num_of_samples):
    """Returns numpya array of all audio signals"""
    all_audio_signals=[]

    for path in ds['file_path']:
        audio= audio_signals("./Dataset-2/"+path)
        all_audio_signals.append(audio)
        if(len(all_audio_signals)==num_of_samples):
            break

    all_audio_signals= np.array(all_audio_signals, dtype=object)
    return all_audio_signals
```

Data augmentation (Data Pre-processing)

In [ ]:

```
import numpy as np
import librosa
import random

def add_noise(audio, noise_factor=0.005):
    """Add random noise to the audio signal"""
    noise = np.random.randn(len(audio))
    augmented_audio = audio + noise_factor * noise
    return augmented_audio

def time_stretch(audio, rate=1.2):
    """Stretch or compress the audio in time without changing pitch"""
    augmented_audio = librosa.effects.time_stretch(y=audio, rate=rate)
    return augmented_audio

def pitch_shift(audio, sr, n_steps=2):
    """Shift the pitch of the audio signal"""
    augmented_audio = librosa.effects.pitch_shift(audio, sr=sr, n_steps=n_steps)
    return augmented_audio

def time_shift(audio, sr, shift_factor=0.2):
    """Shift the audio signal in time"""
    shift_samples = int(shift_factor * len(audio))
    augmented_audio = np.roll(audio, shift_samples)
    return augmented_audio

def apply_augmentation(audio, sr=16000):
    """Apply random augmentation to the audio signal"""
    # augmentation_functions = [add_noise, time_stretch, pitch_shift, time_shift]
    # augmentation_functions = [add_noise, time_stretch, pitch_shift, lambda x: tim
    augmentation_functions = [add_noise, time_stretch, lambda x, sr=sr: pitch_shift
    augmentation_function = random.choice(augmentation_functions)
    augmented_audio = augmentation_function(audio)
    return augmented_audio

def augment_audios(audios):
    """Apply augmentation to a list of audio signals"""
    augmented_audios = []
    for audio in audios:
        augmented_audio = apply_augmentation(audio)
        augmented_audios.append(augmented_audio)
    return np.array(augmented_audios, dtype= object)
```

Label encoding for speakers

In [ ]:

```
def label_encoding(ds, num_of_samples):
    """Label encoding of speakers for classification"""
    labels=[]

    for label in ds['speaker']:
        labels.append(label)

    # Initialize the LabelEncoder
    label_encoder = LabelEncoder()

    # Fit and transform the labels
    y_encoded = label_encoder.fit_transform(labels)

    # Print the mapping between original labels and encoded values
    label_mapping = dict(zip(label_encoder.classes_, label_encoder.transform(label_
    print("Label Mapping:", label_mapping)
```

```
    y_encoded=y_encoded[0:num_of_samples]
    return y_encoded
```

Fourier Magnitude Spectra- Feature Extraction

In [ ]:
```
def feature_extraction(all_audio_signals, num_of_samples):
    """Returns the fourier magnitude spectrum as feature vector"""
    fourier_magnitude=[]
    fixed_num_freq_samples = 24001

    for audio in all_audio_signals[0:num_of_samples]:
        fourier = np.fft.rfft(audio)
        sampling_rate = 16000.0

        num_freq_samples = len(fourier)
        resampled_fourier = np.interp(np.linspace(0, num_freq_samples - 1, fixed_nu
        N = len(audio)
        normalize = N/2
        norm_amplitude = np.abs(resampled_fourier)/normalize
        fourier_magnitude.append(norm_amplitude)


    fourier_magnitude= np.array(fourier_magnitude, dtype=float)

    return fourier_magnitude
```

For Training

In [ ]:
```
ds= load_dataset("./Dataset-2/train.csv")
```

In [ ]:
```
num_of_samples= 3000
audios= load_audio_signals(ds, num_of_samples)
encoded_y= label_encoding(ds,num_of_samples)
print(audios)
print(audios.shape)
```

```
Label Mapping: {'aew': 0, 'ahw': 1, 'aup': 2, 'awb': 3, 'axb': 4, 'bdl': 5, 'clb':
6, 'eey': 7, 'fem': 8, 'gka': 9, 'jmk': 10, 'ksp': 11, 'ljm': 12, 'lnh': 13, 'rm
s': 14, 'rxr': 15, 'slp': 16, 'slt': 17}
[array([0.00521851, 0.0062561 , 0.00543213, ..., 0.        , 0.        ,
        0.        ], dtype=float32)
 array([0.00094604, 0.00115967, 0.00067139, ..., 0.01141357, 0.01730347,
        0.00491333], dtype=float32)
 array([-0.00115967, -0.00143433, -0.00137329, ..., -0.00183105,
        -0.00195312, -0.00183105], dtype=float32)                ...
 array([ 0.00012207,  0.00012207,  0.00039673, ...,  0.06216431,
         0.0015564 , -0.02697754], dtype=float32)
 array([-0.0005188 , -0.0005188 , -0.00048828, ...,  0.        ,
         0.        ,  0.        ], dtype=float32)
 array([-0.00430298, -0.00424194, -0.00469971, ..., -0.0007019 ,
        -0.00048828, -0.0007019 ], dtype=float32)               ]
(3000,)
```

In [ ]:
```
augmented_audios = augment_audios(audios)
print(augmented_audios)
print(augmented_audios.shape)
```

```
[array([-0.05493164, -0.05148315, -0.04650879, ..., -0.05032349,
        -0.05447388, -0.05737305], dtype=float32)
 array([ 0.00094406,  0.00106522,  0.00078033, ..., -0.00802859,
        -0.00226684,  0.00577904], dtype=float32)
 array([ 0.00704814, -0.00129165, -0.00388875, ..., -0.00016747,
        -0.00443582, -0.00039775])                                 ...
 array([7.3119605e-05, 1.9680563e-04, 3.4200089e-04, ..., 2.4078891e-03,
        5.7600420e-03, 3.1722693e-03], dtype=float32)
 array([-0.0004702 , -0.00052782, -0.00049365, ..., -0.00030277,
        -0.00027932, -0.00032359], dtype=float32)
 array([-4.2791897e-03, -4.2221909e-03, -4.6514133e-03, ...,
         1.2576625e-04,  2.8581971e-05, -3.3309010e-05], dtype=float32)]
(3000,)
```

In [ ]:
```
features= feature_extraction(augmented_audios,num_of_samples)
```

For Testing

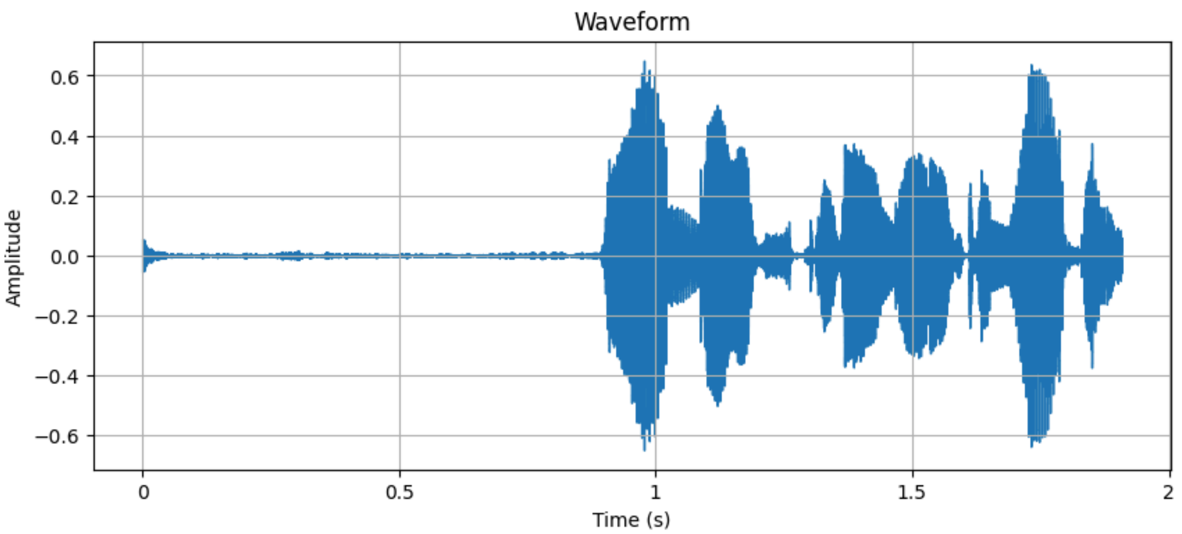
In [ ]:
```
test_ds= load_dataset("./Dataset-2/test_full.csv")
test_audios= load_audio_signals(test_ds,num_of_samples)
encoded_y_test= label_encoding(test_ds,num_of_samples)
features_y= feature_extraction(test_audios,num_of_samples)
```

```
Label Mapping: {'aew': 0, 'ahw': 1, 'aup': 2, 'awb': 3, 'axb': 4, 'bdl': 5, 'clb':
6, 'eey': 7, 'fem': 8, 'gka': 9, 'jmk': 10, 'ksp': 11, 'ljm': 12, 'lnh': 13, 'rm
s': 14, 'rxr': 15, 'slp': 16, 'slt': 17}
```

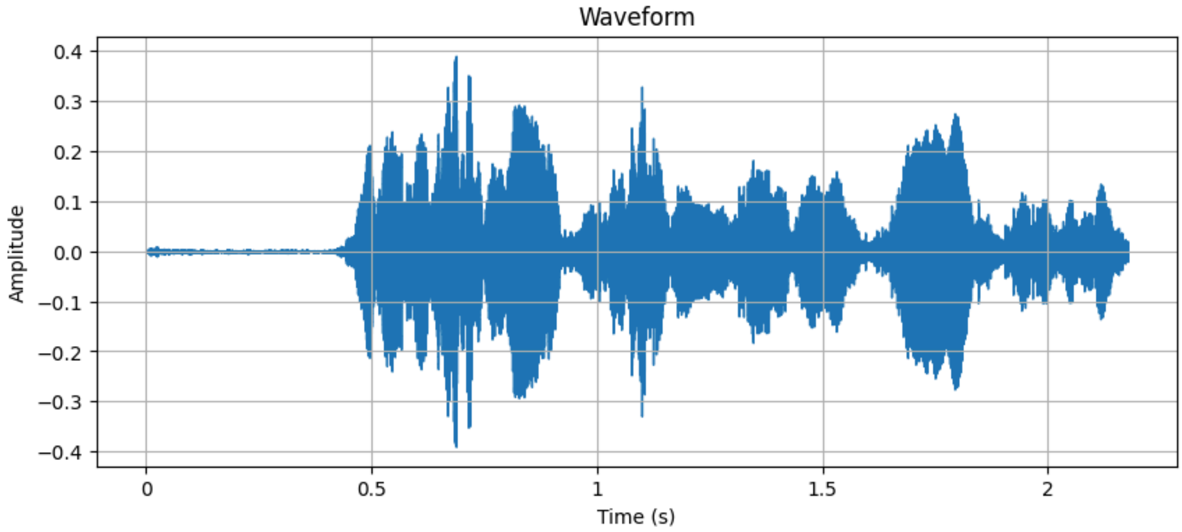
Plots of augmented audios

In [ ]:
```
# plotting first 2 signals

for i in range(2):
    plt.figure()
    #plot the raw audio signal using librosa
    plt.figure(figsize=(10,4))
    librosa.display.waveshow(augmented_audios[i])
    plt.xlabel("Time (s)")
    plt.ylabel("Amplitude")
    plt.title("Waveform")
    plt.grid()
    plt.show()
```

```
<Figure size 640x480 with 0 Axes>
```

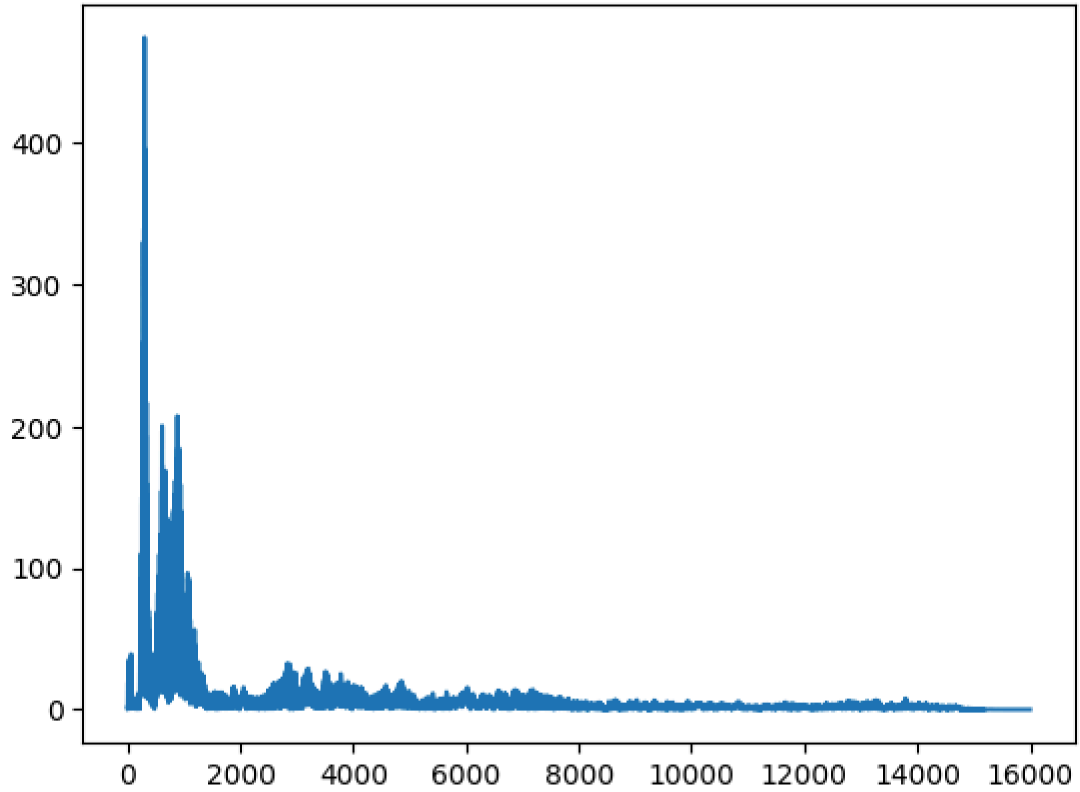


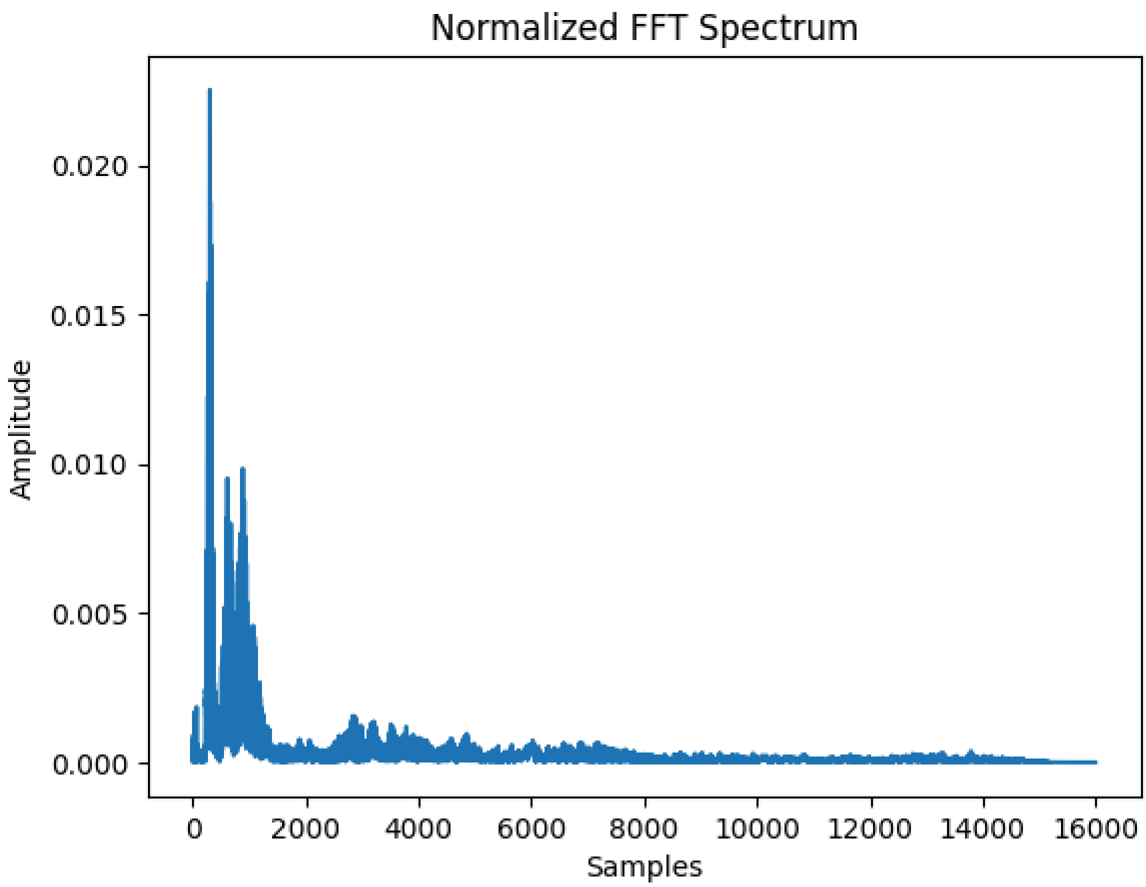

```
<Figure size 640x480 with 0 Axes>
```



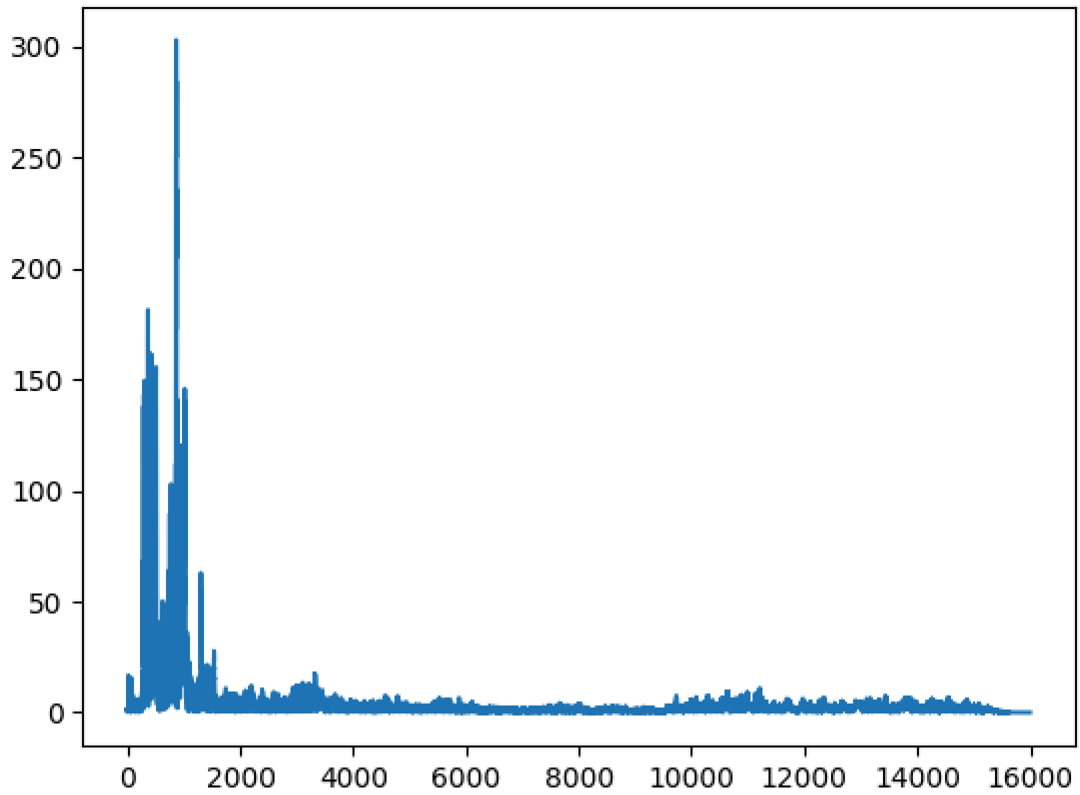
In [ ]:
```
for i in range(2):
    print(f"For speaker {i}")
    fourier = np.fft.rfft(augmented_audios[i])
    # Get the frequency components of the spectrum
    sampling_rate = 16000.0 # It's used as a sample spacing
    frequency_axis = np.linspace(0, sampling_rate, len(np.abs(fourier)))
    plt.figure()
    # Plot the result (the spectrum |Xk|)
    plt.plot(frequency_axis,np.abs(fourier))
    plt.show()

    # Calculate N/2 to normalize the FFT output
    N = len(audios[i])
    normalize = N/2

    plt.figure()
    # Plot the normalized FFT (|Xk|)/(N/2)
    plt.plot(frequency_axis,np.abs(fourier)/normalize)
    plt.ylabel('Amplitude')
    plt.xlabel('Samples')
    plt.title('Normalized FFT Spectrum')
    plt.show()
```

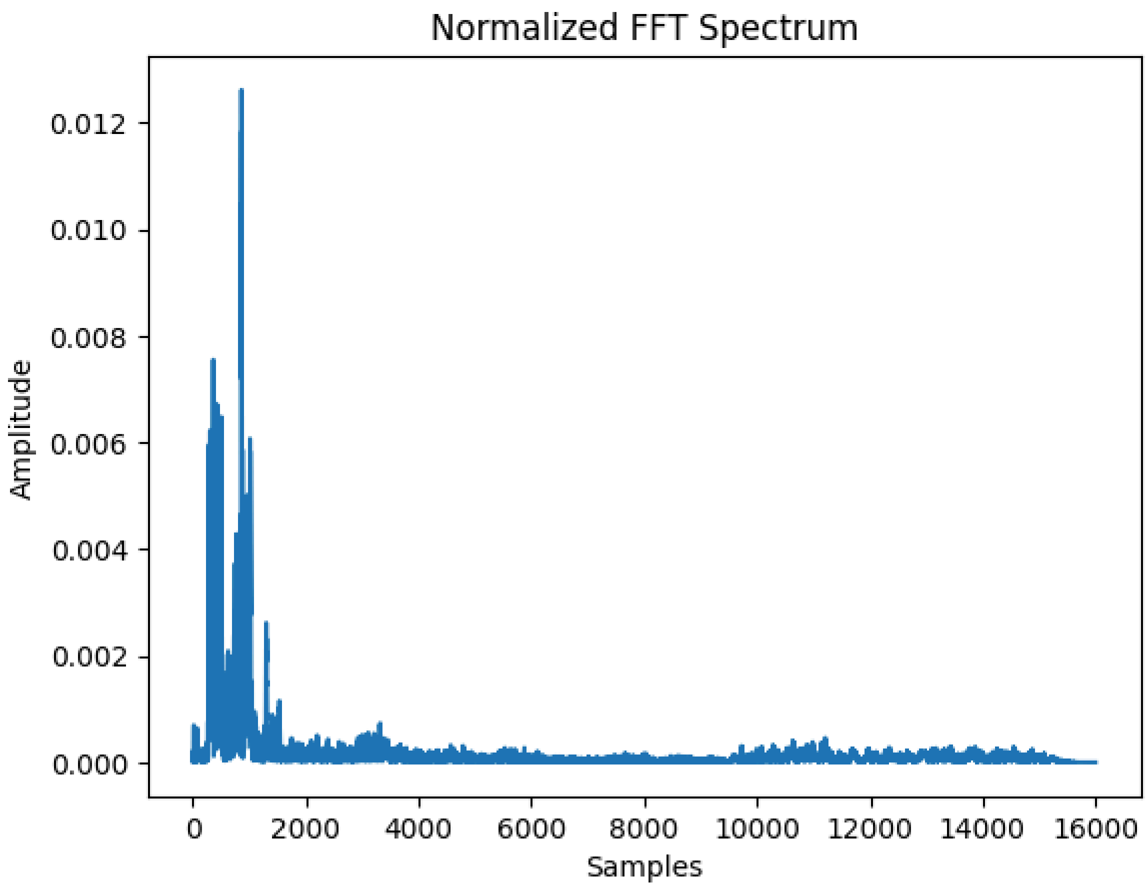
```
For speaker 0
```





For speaker 1





Machine Learning: Logistic Regression

In [ ]:
```
X_train, X_test, y_train, y_test = train_test_split(features, encoded_y, test_size
```

In [ ]:
```
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

In [ ]:
```python
classifier = LogisticRegression(random_state = 0)
classifier.fit(X_train, y_train)
```

Out[ ]:
```
LogisticRegression
LogisticRegression(random_state=0)
```

TESTING

In [ ]:
```python
print(classifier.predict(sc.transform(features_y)))
y_pred=classifier.predict(sc.transform(features_y))
```

```
[ 7  7  3 ... 11  7 15]
```

In [ ]:
```python
y_test=encoded_y_test
print(y_test)
```

```
[ 0  7  3 ... 11  7 15]
```

In [ ]:
```python
cm = confusion_matrix(y_test, y_pred)
print(cm)
print("Accuracy", accuracy_score(y_pred, y_test))
```

```
[[172   4   2   1   7   3   1   6   5   0   1   2   0   4   4   4   2   1]
 [  0 106   0   0   0   0   0   0   1   0   0   4   0   0   0   2   0   0]
 [  0   0 112   0   4   1   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0 213   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0 111   0   0   1   0   0   0   0   0   1   0   0   1   1]
 [  1   1   3   7   1 195   0   2   1   0   2   1   0   3   0   0   0   0]
 [  0   0   0   0   0   1 211   0   0   0   0   0   0   0   0   0   0   8]
 [  0   1   0   0   1   3   1  90   0   0   0   0   3   2   0   0  12   1]
 [  0   0   0   0   1   0   0   0 113   0   0   0   0   0   0   0   0   0]
 [ 16   0   0   0   0   0   0   0   0  91   2   5   0   0   0   1   0   0]
 [  0   0   0   0   0   0   0   0   0   0 218   0   0   0   0   0   0   0]
 [  1   0   0   0   0   0   0   0   0   0   0 217   0   0   0   0   1   0]
 [  0   0   0   0   3   0   2   3   0   0   0   0  78   8   0   0  18   3]
 [  1   0   0   0   0   8   0   0   0   0   0   0   3 201   1   0   2   2]
 [  4   0   1   0   0   0   0   1   1   0   0   0   0   0 205   0   0   0]
 [  1   6   3   0   1   0   0   0   1   1   0   6   0   4   0 104   1   1]
 [  0   0   0   0   3   0   2   3   0   0   0   0   6   0   0   0 100   0]
 [  0   2   0   1   0   0   2   0   1   0   3   0   1   0   0   0   0 208]]
Accuracy 0.915
```

In [ ]:
```python
from sklearn.metrics import classification_report
print(classification_report(y_test,y_pred))
```

	precision	recall	f1-score	support
0	0.88	0.79	0.83	219
1	0.88	0.94	0.91	113
2	0.93	0.96	0.94	117
3	0.96	1.00	0.98	213
4	0.84	0.97	0.90	115
5	0.92	0.90	0.91	217
6	0.96	0.96	0.96	220
7	0.85	0.79	0.82	114
8	0.92	0.99	0.95	114
9	0.99	0.79	0.88	115
10	0.96	1.00	0.98	218
11	0.92	0.99	0.96	219
12	0.86	0.68	0.76	115
13	0.90	0.92	0.91	218
14	0.98	0.97	0.97	212
15	0.94	0.81	0.87	129
16	0.73	0.88	0.80	114
17	0.92	0.95	0.94	218
accuracy			0.92	3000
macro avg	0.91	0.90	0.90	3000
weighted avg	0.92	0.92	0.91	3000

In [ ]:

```
from sklearn.metrics import precision_recall_fscore_support
res = []
for l in range(18):
     prec,recall,_,_ = precision_recall_fscore_support(np.array(y_test)==l,
                                                       np.array(y_pred)==l,
                                                       pos_label=True,average=None)
     res.append([l,recall[0],recall[1]])

pd.DataFrame(res,columns = ['class','specificity','sensitivity'])
```

Out[ ]:

	class	specificity	sensitivity
0	0	0.991370	0.785388
1	1	0.995151	0.938053
2	2	0.996878	0.957265
3	3	0.996771	1.000000
4	4	0.992721	0.965217
5	5	0.994251	0.898618
6	6	0.997122	0.959091
7	7	0.994456	0.789474
8	8	0.996535	0.991228
9	9	0.999653	0.791304
10	10	0.997124	1.000000
11	11	0.993528	0.990868
12	12	0.995494	0.678261
13	13	0.992092	0.922018
14	14	0.998207	0.966981
15	15	0.997562	0.806202
16	16	0.987179	0.877193
17	17	0.993889	0.954128

1D CNN without Windowing

In [ ]:

```
X_train, X_temp, y_train, y_temp = train_test_split(features, encoded_y, test_size=
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5, ranc

X_train = X_train.astype('float32')
y_train = y_train.astype('int32')
X_val = X_val.astype('float32')
y_val = y_val.astype('int32')
X_test = X_test.astype('float32')
y_test = y_test.astype('int32')

# Print the shapes of training and validation data
print("Training Data Shape:", X_train.shape)
print("Validation Data Shape:", X_val.shape)
print("Test Data Shape:", X_test.shape)

print("Training y Data Shape:", y_train.shape)
print("Validation y Data Shape:", y_val.shape)
print("Test y Data Shape:", y_test.shape)
```

```
Training Data Shape: (2100, 24001)
Validation Data Shape: (450, 24001)
Test Data Shape: (450, 24001)
Training y Data Shape: (2100,)
Validation y Data Shape: (450,)
Test y Data Shape: (450,)
```

In [ ]:

```
# Reshape the input data for compatibility with Conv1D
X_train_reshaped = X_train.reshape(X_train.shape[0], X_train.shape[1], 1)
X_val_reshaped = X_val.reshape(X_val.shape[0], X_val.shape[1], 1)

# Convert labels to one-hot encoded format
num_classes = len(np.unique(y_train))
y_train_encoded = to_categorical(y_train, num_classes=num_classes)
y_val_encoded = to_categorical(y_val, num_classes=num_classes)

# Defining the CNN model
model = Sequential([
    Conv1D(64, kernel_size=3, activation='relu', input_shape=(X_train.shape[1], 1))
    MaxPooling1D(pool_size=2),
    Conv1D(128, kernel_size=3, activation='relu'),
    MaxPooling1D(pool_size=2),
    Flatten(),
    Dense(64, activation='relu'),
    Dense(num_classes, activation='softmax')
])

model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy

model.summary()

history = model.fit(X_train_reshaped, y_train_encoded, validation_data=(X_val_resha

model.save("1d_cnn_model_without_window_new.h5")
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_2 (Conv1D)           (None, 23999, 64)         256

 max_pooling1d_2 (MaxPooling  (None, 11999, 64)        0
 1D)

 conv1d_3 (Conv1D)           (None, 11997, 128)        24704

 max_pooling1d_3 (MaxPooling  (None, 5998, 128)        0
 1D)

 flatten_1 (Flatten)         (None, 767744)            0

 dense_2 (Dense)             (None, 64)                49135680

 dense_3 (Dense)             (None, 18)                1170

=================================================================
Total params: 49,161,810
Trainable params: 49,161,810
Non-trainable params: 0
_________________________________________________________________
```

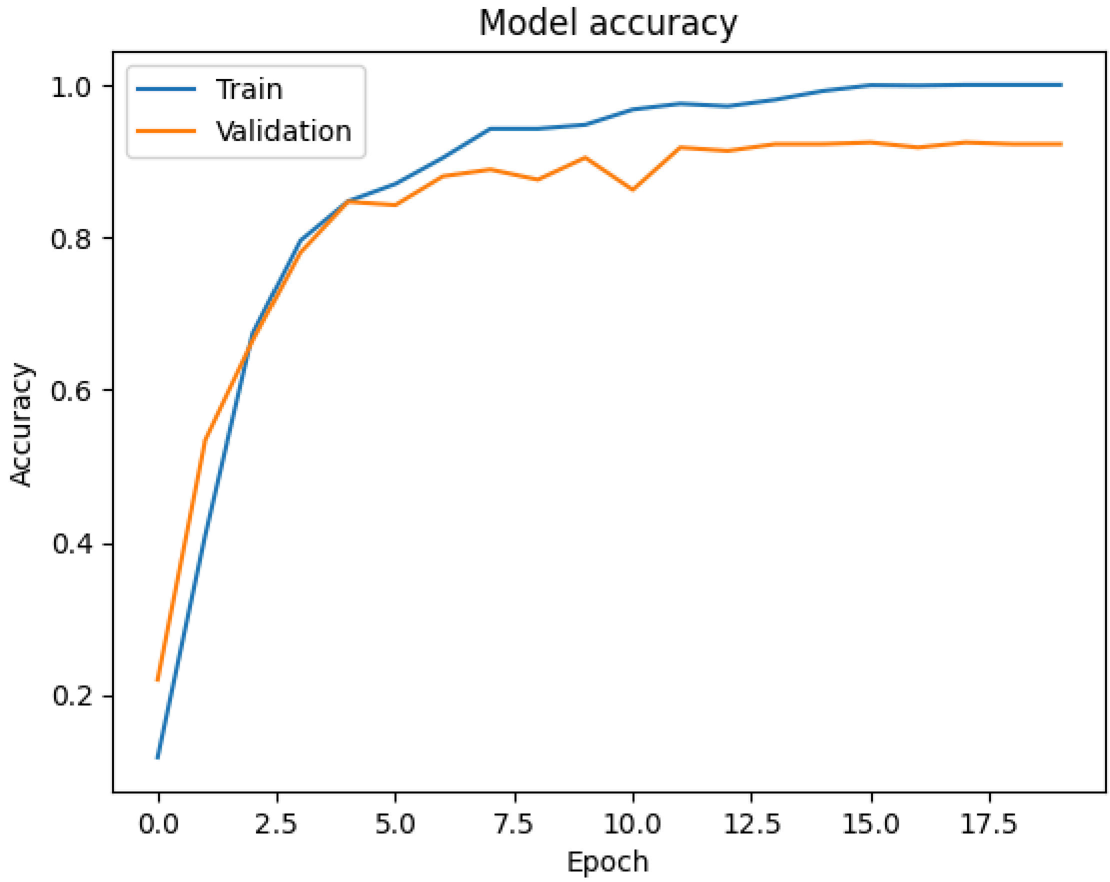

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_2 (Conv1D)           (None, 23999, 64)         256

 max_pooling1d_2 (MaxPooling  (None, 11999, 64)        0
 1D)

 conv1d_3 (Conv1D)           (None, 11997, 128)        24704

 max_pooling1d_3 (MaxPooling  (None, 5998, 128)        0
 1D)

 flatten_1 (Flatten)         (None, 767744)            0

 dense_2 (Dense)             (None, 64)                49135680

 dense_3 (Dense)             (None, 18)                1170

=================================================================
Total params: 49,161,810
Trainable params: 49,161,810
Non-trainable params: 0
_________________________________________________________________
```

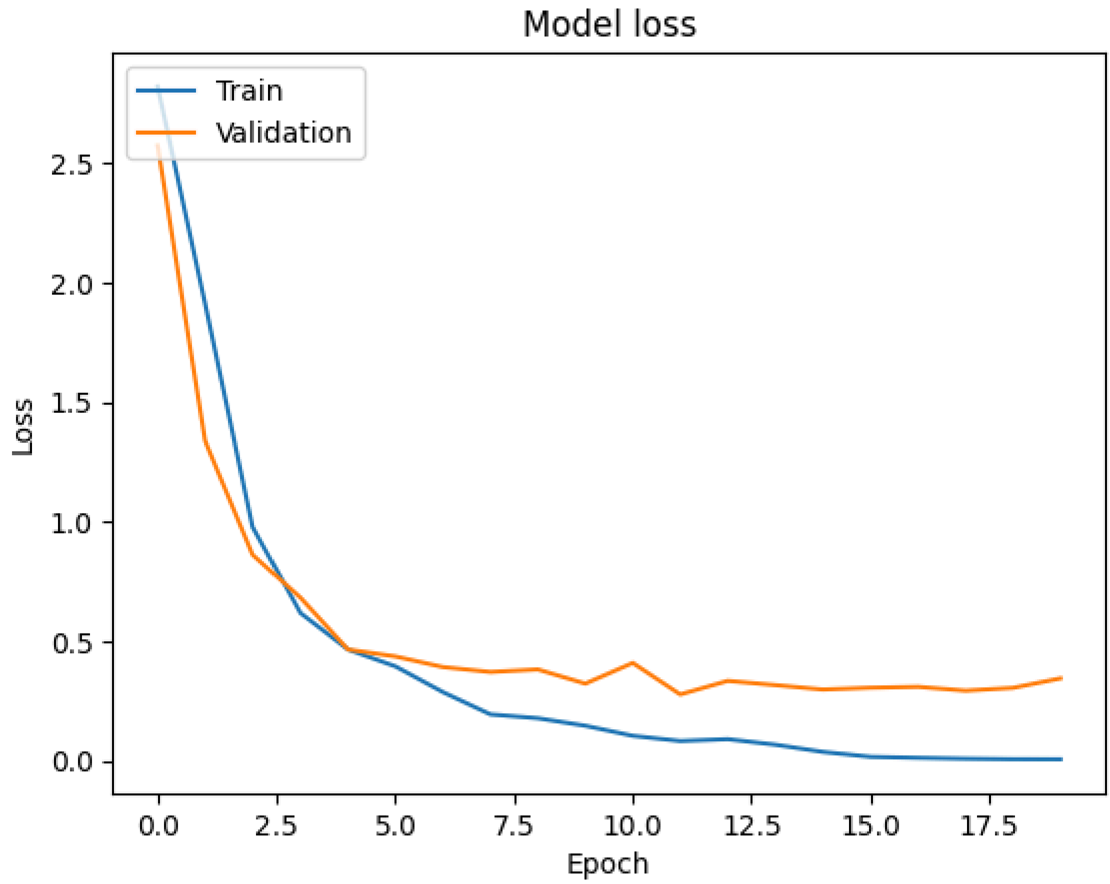

```
Epoch 1/20
66/66 [==============================] - 151s 2s/step - loss: 2.8230 - accuracy:
0.1181 - val_loss: 2.5752 - val_accuracy: 0.2200
Epoch 2/20
66/66 [==============================] - 135s 2s/step - loss: 1.9129 - accuracy:
0.4086 - val_loss: 1.3391 - val_accuracy: 0.5333
Epoch 3/20
66/66 [==============================] - 134s 2s/step - loss: 0.9789 - accuracy:
0.6738 - val_loss: 0.8625 - val_accuracy: 0.6644
Epoch 4/20
66/66 [==============================] - 142s 2s/step - loss: 0.6184 - accuracy:
0.7957 - val_loss: 0.6828 - val_accuracy: 0.7800
Epoch 5/20
66/66 [==============================] - 145s 2s/step - loss: 0.4659 - accuracy:
0.8471 - val_loss: 0.4657 - val_accuracy: 0.8467
```

```
Epoch 6/20
66/66 [==============================] - 156s 2s/step - loss: 0.3950 - accuracy:
0.8700 - val_loss: 0.4366 - val_accuracy: 0.8422
Epoch 7/20
66/66 [==============================] - 142s 2s/step - loss: 0.2873 - accuracy:
0.9043 - val_loss: 0.3922 - val_accuracy: 0.8800
Epoch 8/20
66/66 [==============================] - 146s 2s/step - loss: 0.1939 - accuracy:
0.9424 - val_loss: 0.3715 - val_accuracy: 0.8889
Epoch 9/20
66/66 [==============================] - 145s 2s/step - loss: 0.1778 - accuracy:
0.9424 - val_loss: 0.3822 - val_accuracy: 0.8756
Epoch 10/20
66/66 [==============================] - 143s 2s/step - loss: 0.1463 - accuracy:
0.9476 - val_loss: 0.3227 - val_accuracy: 0.9044
Epoch 11/20
66/66 [==============================] - 139s 2s/step - loss: 0.1041 - accuracy:
0.9676 - val_loss: 0.4096 - val_accuracy: 0.8622
Epoch 12/20
66/66 [==============================] - 135s 2s/step - loss: 0.0824 - accuracy:
0.9752 - val_loss: 0.2775 - val_accuracy: 0.9178
Epoch 13/20
66/66 [==============================] - 132s 2s/step - loss: 0.0901 - accuracy:
0.9719 - val_loss: 0.3343 - val_accuracy: 0.9133
Epoch 14/20
66/66 [==============================] - 132s 2s/step - loss: 0.0669 - accuracy:
0.9805 - val_loss: 0.3166 - val_accuracy: 0.9222
Epoch 15/20
66/66 [==============================] - 1578s 24s/step - loss: 0.0368 - accuracy:
0.9919 - val_loss: 0.2981 - val_accuracy: 0.9222
Epoch 16/20
66/66 [==============================] - 154s 2s/step - loss: 0.0160 - accuracy:
0.9995 - val_loss: 0.3055 - val_accuracy: 0.9244
Epoch 17/20
66/66 [==============================] - 146s 2s/step - loss: 0.0117 - accuracy:
0.9990 - val_loss: 0.3093 - val_accuracy: 0.9178
Epoch 18/20
66/66 [==============================] - 141s 2s/step - loss: 0.0082 - accuracy:
1.0000 - val_loss: 0.2933 - val_accuracy: 0.9244
Epoch 19/20
66/66 [==============================] - 142s 2s/step - loss: 0.0062 - accuracy:
1.0000 - val_loss: 0.3050 - val_accuracy: 0.9222
Epoch 20/20
66/66 [==============================] - 130s 2s/step - loss: 0.0058 - accuracy:
1.0000 - val_loss: 0.3447 - val_accuracy: 0.9222
```

In [ ]:

```python
# Plot training & validation accuracy values
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(['Train', 'Validation'], loc='upper left')
plt.show()

# Plot training & validation loss values
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend(['Train', 'Validation'], loc='upper left')
plt.show()
```





TESTING

In [ ]:
```
loaded_model = load_model("1d_cnn_model_without_window_new.h5")

X_test_reshaped = features_y.reshape(features_y.shape[0], features_y.shape[1], 1)
```

```python
y_pred = loaded_model.predict(X_test_reshaped)
```

```
94/94 [==============================] - 46s 491ms/step
```

In [ ]:
```python
y_pred_classes = np.argmax(y_pred, axis=1)
print(y_pred_classes)
```

```
[ 0  7  3 ... 11  7 15]
```

In [ ]:
```python
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(encoded_y_test, y_pred_classes)
print(cm)
accuracy_score(encoded_y_test, y_pred_classes)
```

```
[[193   0   3   0   0   0   0   0   6   2   1   6   0   0   8   0   0   0]
 [  0 105   0   1   0   0   0   0   0   0   0   7   0   0   0   0   0   0]
 [  1   0 113   1   0   1   0   0   0   0   1   0   0   0   0   0   0   0]
 [  0   0   0 213   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   2   0  91   0   0   3   0   0   0   0   8   2   0   0   6   3]
 [  0   1  14   6   0 182   0   0  12   0   0   0   0   2   0   0   0   0]
 [  0   0   0   0   0   0 212   0   0   0   0   0   0   0   0   0   0   8]
 [  0   0   0   0   0   0   3  96   0   0   0   0   2   0   0   0   8   5]
 [  0   0   0   0   0   0   0   0 106   0   0   0   0   0   8   0   0   0]
 [  0   0   0   0   0   0   0   0   0 106   8   0   0   0   1   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0 217   0   0   0   1   0   0   0]
 [  3  10   0   0   0   3   0   0   2   5   1 195   0   0   0   0   0   0]
 [  0   0   0   0   2   0   0  10   0   0   0   0  66  14   0   1  13   9]
 [  1   0   3   0   0   0   0   2   0   0   0   0   0 206   0   3   2   1]
 [  1   0   0   0   0   0   0   0   0   0   0   0   0   0 211   0   0   0]
 [  0   6   0   0   0   0   0   0   0   1   0   4   0   2   0 116   0   0]
 [  0   0   0   0   2   0   3  25   0   0   0   0   9   0   0   0  72   3]
 [  0   0   2   2   0   0   2   1   0   0   0   6   1   0   0   1   0 203]]
```

Out[ ]:
```
0.901
```

In [ ]:
```python
from sklearn.metrics import classification_report
print(classification_report(encoded_y_test,y_pred_classes))
```

```
              precision    recall  f1-score   support

           0       0.97      0.88      0.92       219
           1       0.86      0.93      0.89       113
           2       0.82      0.97      0.89       117
           3       0.96      1.00      0.98       213
           4       0.96      0.79      0.87       115
           5       0.98      0.84      0.90       217
           6       0.96      0.96      0.96       220
           7       0.70      0.84      0.76       114
           8       0.84      0.93      0.88       114
           9       0.93      0.92      0.93       115
          10       0.95      1.00      0.97       218
          11       0.89      0.89      0.89       219
          12       0.77      0.57      0.66       115
          13       0.91      0.94      0.93       218
          14       0.92      1.00      0.96       212
          15       0.96      0.90      0.93       129
          16       0.71      0.63      0.67       114
          17       0.88      0.93      0.90       218

    accuracy                           0.90      3000
   macro avg       0.89      0.88      0.88      3000
weighted avg       0.90      0.90      0.90      3000
```

In [ ]:
```
from sklearn.metrics import precision_recall_fscore_support
res = []
for l in range(18):
     prec,recall,_,_ = precision_recall_fscore_support(np.array(encoded_y_test)==l,
                                                        np.array(y_pred_classes)==l,
                                                        pos_label=True,average=None)
     res.append([l,recall[0],recall[1]])

pd.DataFrame(res,columns = ['class','specificity','sensitivity'])
```

Out[ ]:

	class	specificity	sensitivity
0	0	0.997843	0.881279
1	1	0.994112	0.929204
2	2	0.991675	0.965812
3	3	0.996412	1.000000
4	4	0.998614	0.791304
5	5	0.998563	0.838710
6	6	0.997122	0.963636
7	7	0.985793	0.842105
8	8	0.993070	0.929825
9	9	0.997227	0.921739
10	10	0.996046	0.995413
11	11	0.991730	0.890411
12	12	0.993068	0.573913
13	13	0.992811	0.944954
14	14	0.993544	0.995283
15	15	0.998258	0.899225
16	16	0.989951	0.631579
17	17	0.989576	0.931193

1D CNN with hamming window

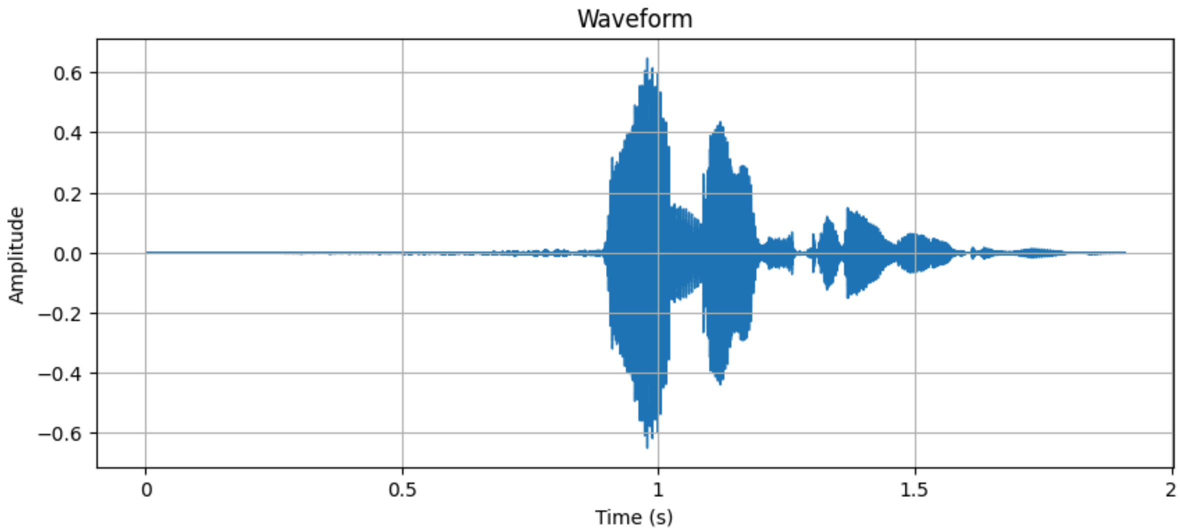
In [ ]:
```
def apply_window(audio, window_type="hamming"):
    if window_type == "hamming":
        window = np.hamming(len(audio))
    else:
        raise ValueError("Invalid window type. Supported type is 'hamming'.")

    # Apply the window to the audio signal
    windowed_audio = audio * window
    return windowed_audio
```

In [ ]:
```
augmented_audios=[apply_window(audio, window_type="hamming") for audio in augmented
features= feature_extraction(augmented_audios,num_of_samples)
```

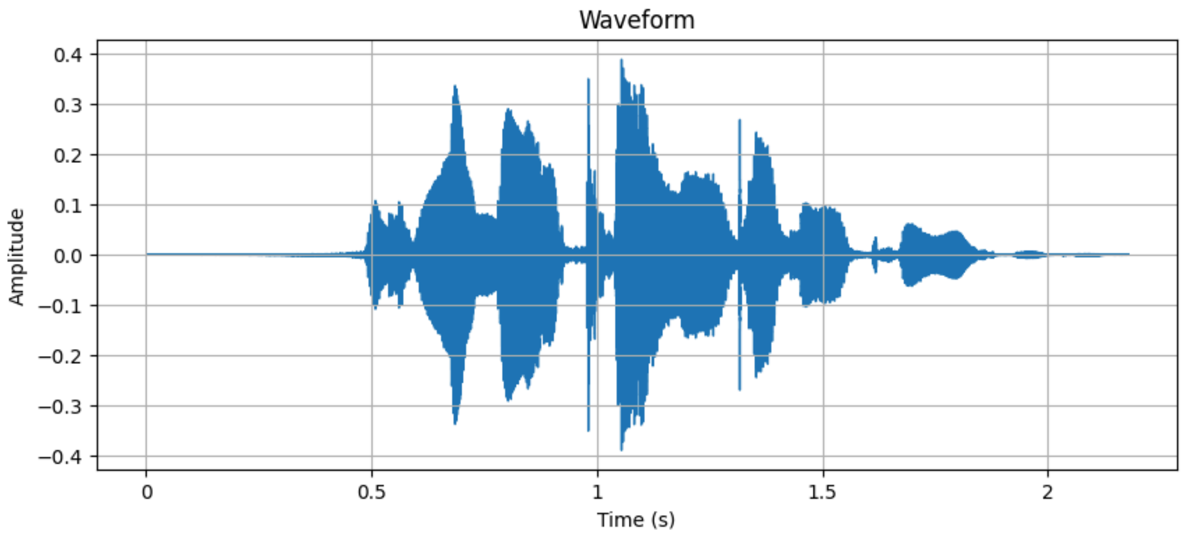
Plots with windowed audios

In [ ]:
```
for i in range(2):
    plt.figure()
    #plot the raw audio signal using librosa
    plt.figure(figsize=(10,4))
    librosa.display.waveshow(augmented_audios[i])
    plt.xlabel("Time (s)")
    plt.ylabel("Amplitude")
    plt.title("Waveform")
    plt.grid()
    plt.show()
```

```
<Figure size 640x480 with 0 Axes>
```



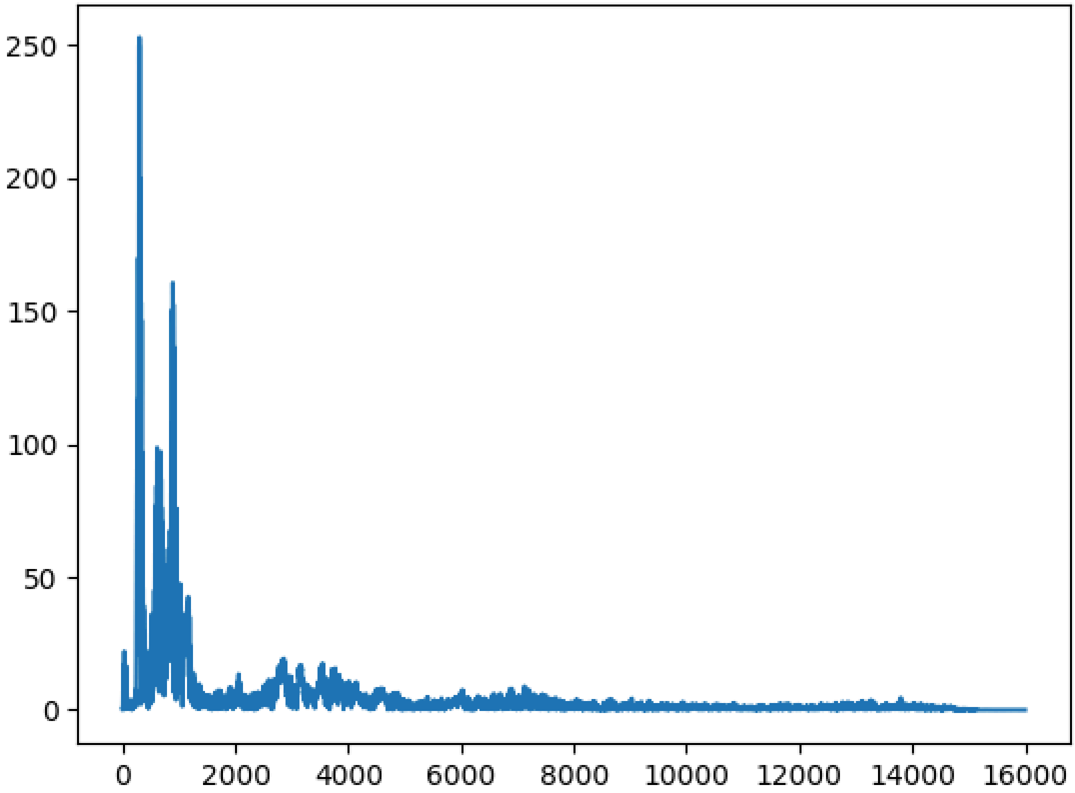

```
<Figure size 640x480 with 0 Axes>
```

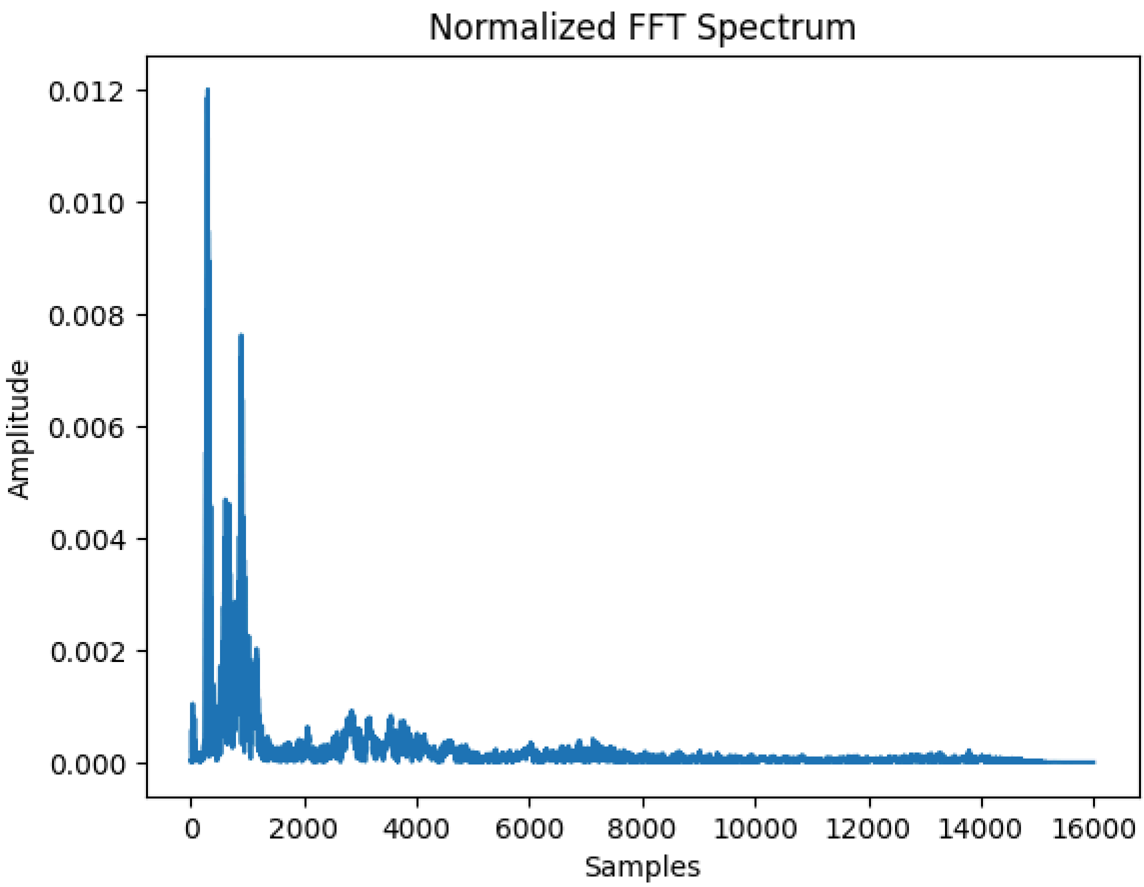


In [ ]:
```
for i in range(2):
    print(f"For speaker {i}")
    fourier = np.fft.rfft(augmented_audios[i])
    # Get the frequency components of the spectrum
    sampling_rate = 16000.0 # It's used as a sample spacing
    frequency_axis = np.linspace(0, sampling_rate, len(np.abs(fourier)))
    plt.figure()
    # Plot the result (the spectrum |Xk|)
    plt.plot(frequency_axis,np.abs(fourier))
    plt.show()

    # Calculate N/2 to normalize the FFT output
    N = len(audios[i])
    normalize = N/2
```

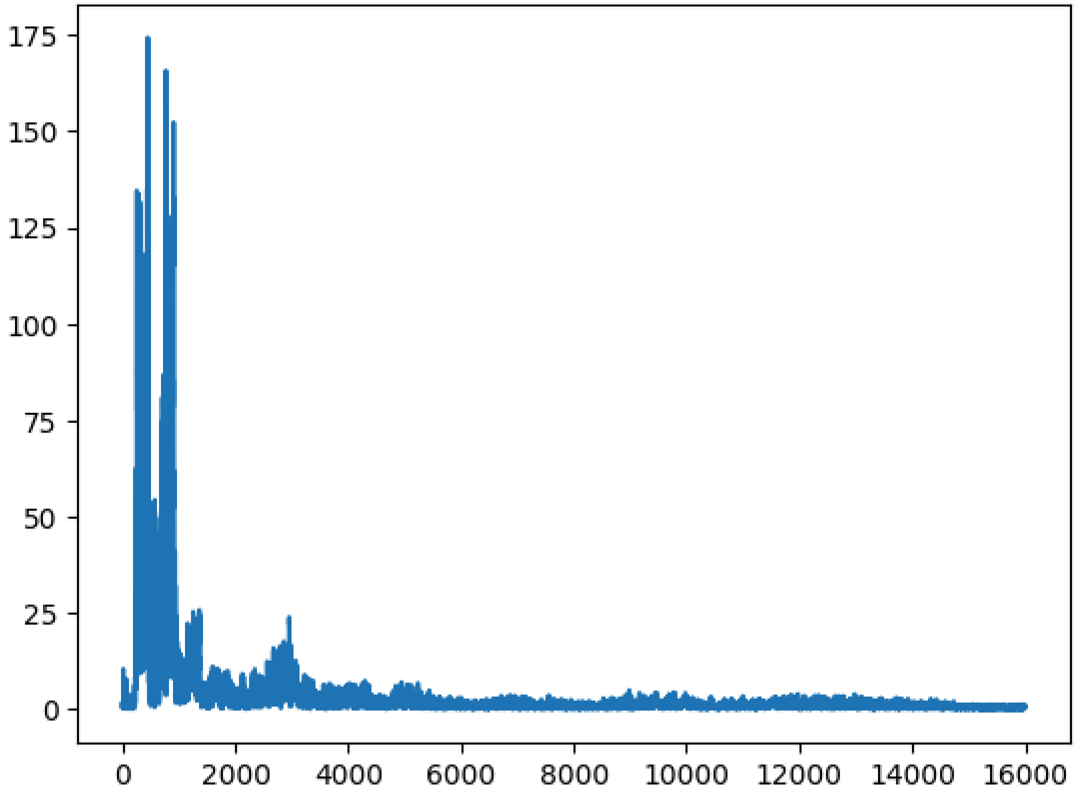
```python
    plt.figure()
    # Plot the normalized FFT (|Xk|)/(N/2)
    plt.plot(frequency_axis,np.abs(fourier)/normalize)
    plt.ylabel('Amplitude')
    plt.xlabel('Samples')
    plt.title('Normalized FFT Spectrum')
    plt.show()
```

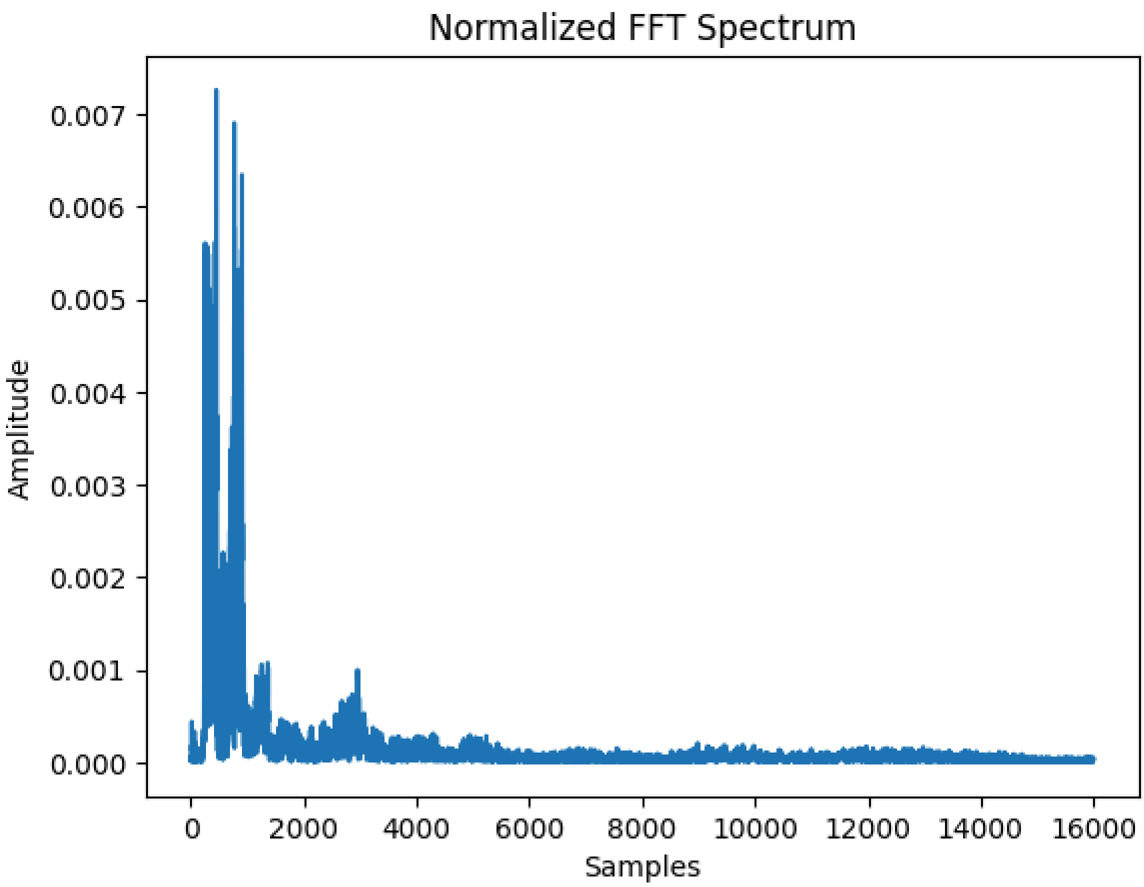
For speaker 0





For speaker 1





In [ ]:

```
# Split the data into training, validation, and test sets
X_train, X_temp, y_train, y_temp = train_test_split(features, encoded_y, test_size=
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5, ranc


X_train = X_train.astype('float32')
y_train = y_train.astype('int32')
X_val = X_val.astype('float32')
y_val = y_val.astype('int32')
```

```
X_test = X_test.astype('float32')
y_test = y_test.astype('int32')

# Print the shapes of training and validation data
print("Training Data Shape:", X_train.shape)
print("Validation Data Shape:", X_val.shape)
print("Test Data Shape:", X_test.shape)

print("Training y Data Shape:", y_train.shape)
print("Validation y Data Shape:", y_val.shape)
print("Test y Data Shape:", y_test.shape)
```

```
Training Data Shape: (2100, 24001)
Validation Data Shape: (450, 24001)
Test Data Shape: (450, 24001)
Training y Data Shape: (2100,)
Validation y Data Shape: (450,)
Test y Data Shape: (450,)
```

In [ ]:

```
# Reshape the input data for compatibility with Conv1D
X_train_reshaped = X_train.reshape(X_train.shape[0], X_train.shape[1], 1)
X_val_reshaped = X_val.reshape(X_val.shape[0], X_val.shape[1], 1)

# Convert labels to one-hot encoded format
num_classes = len(np.unique(y_train))
y_train_encoded = to_categorical(y_train, num_classes=num_classes)
y_val_encoded = to_categorical(y_val, num_classes=num_classes)

# Defining the CNN model
model = Sequential([
    Conv1D(64, kernel_size=3, activation='relu', input_shape=(X_train.shape[1], 1)),
    MaxPooling1D(pool_size=2),
    Conv1D(128, kernel_size=3, activation='relu'),
    MaxPooling1D(pool_size=2),
    Flatten(),
    Dense(64, activation='relu'),
    Dense(num_classes, activation='softmax')
])

model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy

model.summary()

history = model.fit(X_train_reshaped, y_train_encoded, validation_data=(X_val_resha

model.save("1d_cnn_model_hamming_window_new.h5")
```

```
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_10 (Conv1D)          (None, 23999, 64)         256

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_10 (Conv1D)          (None, 23999, 64)         256

 max_pooling1d_10 (MaxPoolin  (None, 11999, 64)        0
 g1D)

 conv1d_11 (Conv1D)          (None, 11997, 128)        24704

 max_pooling1d_11 (MaxPoolin  (None, 5998, 128)        0
 g1D)

 flatten_5 (Flatten)         (None, 767744)            0

 dense_10 (Dense)            (None, 64)                49135680

 dense_11 (Dense)            (None, 18)                1170

=================================================================
Total params: 49,161,810
Trainable params: 49,161,810
Non-trainable params: 0
_________________________________________________________________
Epoch 1/25
66/66 [==============================] - 190s 3s/step - loss: 2.8711 - accuracy:
0.0700 - val_loss: 2.8470 - val_accuracy: 0.0689
Epoch 2/25
66/66 [==============================] - 168s 3s/step - loss: 2.8531 - accuracy:
0.0705 - val_loss: 2.8466 - val_accuracy: 0.0711
Epoch 3/25
66/66 [==============================] - 173s 3s/step - loss: 2.8454 - accuracy:
0.0814 - val_loss: 2.8320 - val_accuracy: 0.1444
Epoch 4/25
66/66 [==============================] - 179s 3s/step - loss: 2.6823 - accuracy:
0.1705 - val_loss: 2.3973 - val_accuracy: 0.2800
Epoch 5/25
66/66 [==============================] - 174s 3s/step - loss: 1.7520 - accuracy:
0.4686 - val_loss: 1.3742 - val_accuracy: 0.5711
Epoch 6/25
66/66 [==============================] - 167s 3s/step - loss: 1.2066 - accuracy:
0.6238 - val_loss: 1.2749 - val_accuracy: 0.5756
Epoch 7/25
66/66 [==============================] - 156s 2s/step - loss: 0.8624 - accuracy:
0.7233 - val_loss: 0.9356 - val_accuracy: 0.6822
Epoch 8/25
66/66 [==============================] - 141s 2s/step - loss: 0.7111 - accuracy:
0.7762 - val_loss: 0.7188 - val_accuracy: 0.7644
Epoch 9/25
66/66 [==============================] - 141s 2s/step - loss: 0.5716 - accuracy:
0.8162 - val_loss: 0.7168 - val_accuracy: 0.7556
Epoch 10/25
66/66 [==============================] - 139s 2s/step - loss: 0.4749 - accuracy:
0.8524 - val_loss: 0.7868 - val_accuracy: 0.7333
Epoch 11/25
66/66 [==============================] - 140s 2s/step - loss: 0.4106 - accuracy:
0.8629 - val_loss: 0.5235 - val_accuracy: 0.8422
Epoch 12/25
66/66 [==============================] - 141s 2s/step - loss: 0.3372 - accuracy:
```

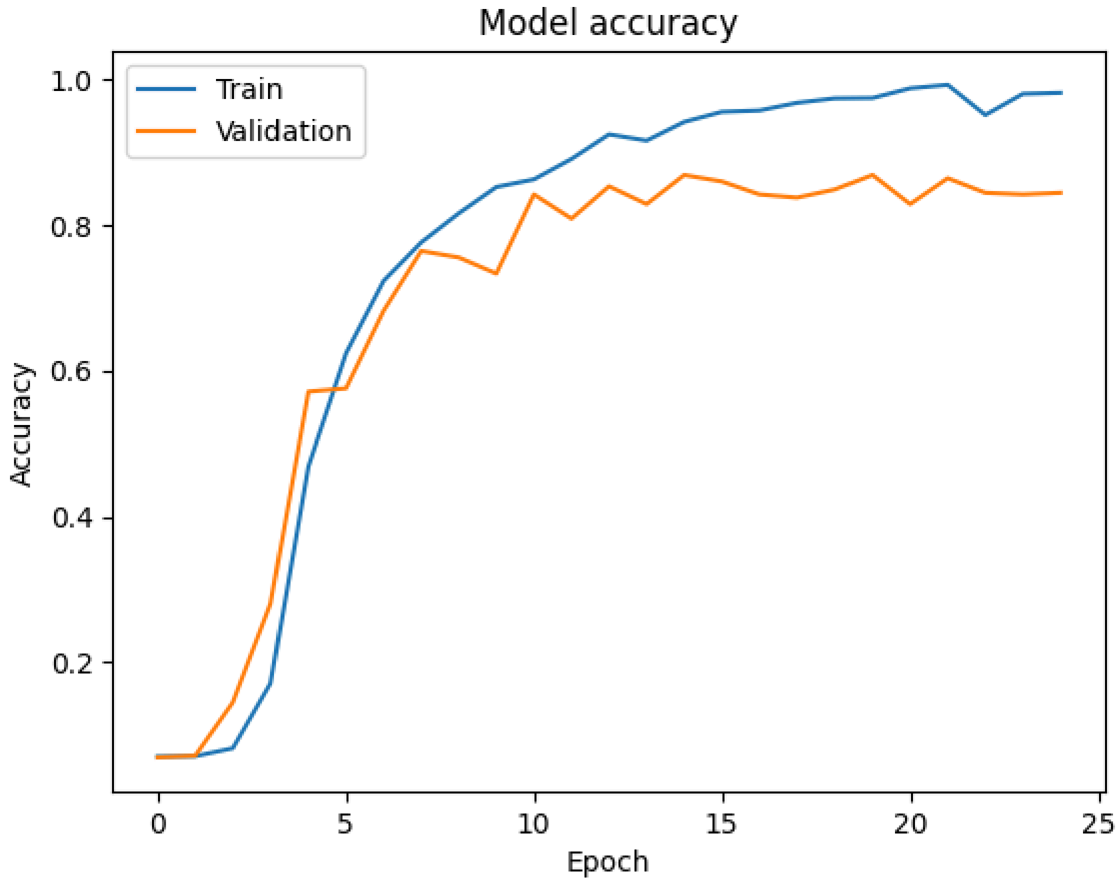
```
0.8910 - val_loss: 0.5334 - val_accuracy: 0.8089
Epoch 13/25
66/66 [==============================] - 141s 2s/step - loss: 0.2641 - accuracy: 
0.9248 - val_loss: 0.4321 - val_accuracy: 0.8533
Epoch 14/25
66/66 [==============================] - 141s 2s/step - loss: 0.2650 - accuracy: 
0.9162 - val_loss: 0.5273 - val_accuracy: 0.8289
Epoch 15/25
66/66 [==============================] - 139s 2s/step - loss: 0.1946 - accuracy: 
0.9419 - val_loss: 0.4189 - val_accuracy: 0.8689
Epoch 16/25
66/66 [==============================] - 140s 2s/step - loss: 0.1492 - accuracy: 
0.9557 - val_loss: 0.4318 - val_accuracy: 0.8600
Epoch 17/25
66/66 [==============================] - 139s 2s/step - loss: 0.1355 - accuracy: 
0.9576 - val_loss: 0.4981 - val_accuracy: 0.8422
Epoch 18/25
66/66 [==============================] - 139s 2s/step - loss: 0.1208 - accuracy: 
0.9681 - val_loss: 0.5594 - val_accuracy: 0.8378
Epoch 19/25
66/66 [==============================] - 140s 2s/step - loss: 0.0958 - accuracy: 
0.9743 - val_loss: 0.4734 - val_accuracy: 0.8489
Epoch 20/25
66/66 [==============================] - 140s 2s/step - loss: 0.0914 - accuracy: 
0.9748 - val_loss: 0.4158 - val_accuracy: 0.8689
Epoch 21/25
66/66 [==============================] - 140s 2s/step - loss: 0.0597 - accuracy: 
0.9881 - val_loss: 0.5404 - val_accuracy: 0.8289
Epoch 22/25
66/66 [==============================] - 140s 2s/step - loss: 0.0468 - accuracy: 
0.9929 - val_loss: 0.4779 - val_accuracy: 0.8644
Epoch 23/25
66/66 [==============================] - 141s 2s/step - loss: 0.1601 - accuracy: 
0.9514 - val_loss: 0.5095 - val_accuracy: 0.8444
Epoch 24/25
66/66 [==============================] - 140s 2s/step - loss: 0.0795 - accuracy: 
0.9805 - val_loss: 0.5467 - val_accuracy: 0.8422
Epoch 25/25
66/66 [==============================] - 140s 2s/step - loss: 0.0667 - accuracy: 
0.9819 - val_loss: 0.5163 - val_accuracy: 0.8444
```

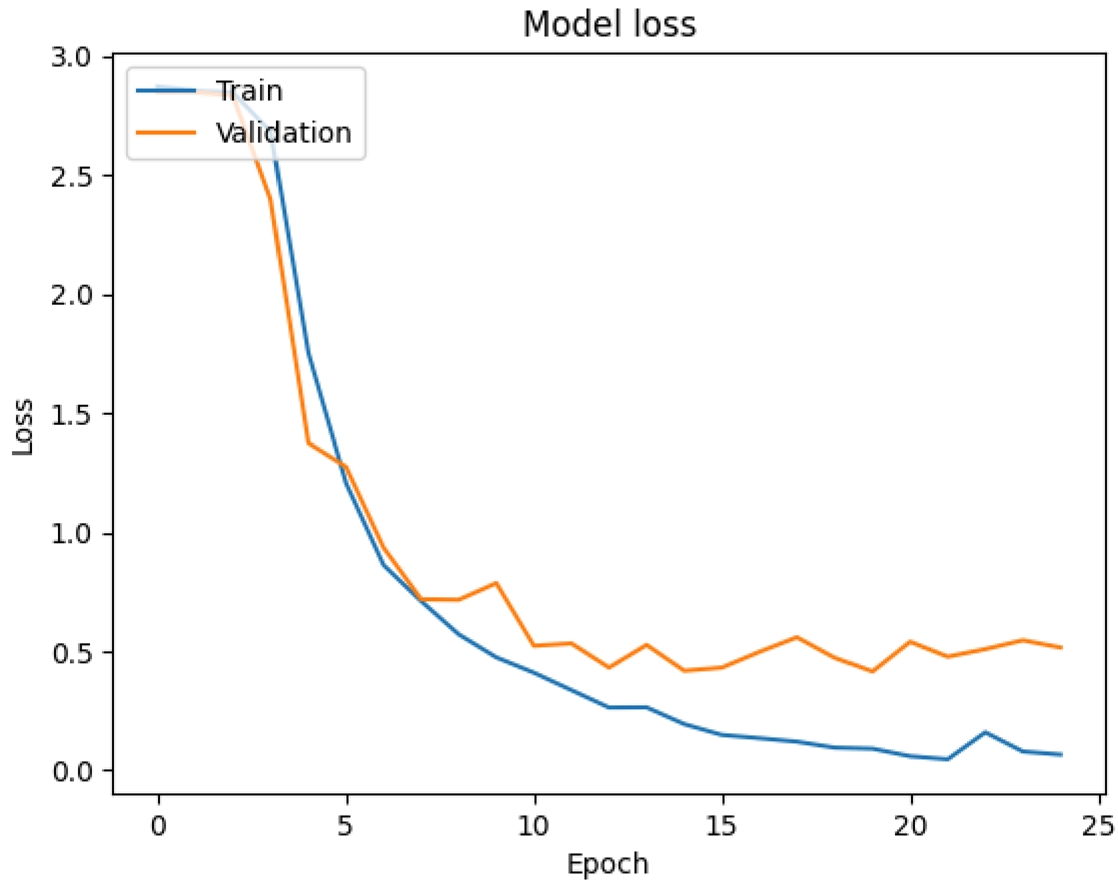
In [ ]:

```
model.save("1d_cnn_model_hamming_window_new.h5")
```

In [ ]:

```
# Plot training & validation accuracy values
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(['Train', 'Validation'], loc='upper left')
plt.show()

# Plot training & validation loss values
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend(['Train', 'Validation'], loc='upper left')
plt.show()
```





TESTING

In [ ]:

```
test_audios=[apply_window(audio, window_type="hamming") for audio in test_audios]
features_y= feature_extraction(test_audios,num_of_samples)
```

In [ ]:
```
loaded_model = load_model("1d_cnn_model_hamming_window_new.h5")

X_test_reshaped = features_y.reshape(features_y.shape[0], features_y.shape[1], 1)

y_pred = loaded_model.predict(X_test_reshaped)
```

```
94/94 [==============================] - 40s 422ms/step
```

In [ ]:
```
y_pred_classes = np.argmax(y_pred, axis=1)
print(y_pred_classes)
```

```
[ 0  7  3 ... 11 16 15]
```

In [ ]:
```
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(encoded_y_test, y_pred_classes)
print(cm)
print("Accuracy:", accuracy_score(encoded_y_test, y_pred_classes))
```

```
[[194   0   2   1   0   0   0   0   8   4   1   6   0   0   3   0   0   0]
 [  0  84   0   3   0   0   0   0   1   0   1  21   0   0   0   3   0   0]
 [  1   0 109   5   0   2   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0 209   0   2   0   0   2   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0  99   0   0   0   0   0   0   0   1   3   0   0   9   3]
 [  0   1   5   6   0 186   0   0  19   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0 209   0   0   1   0   0   0   0   0   0   0  10]
 [  0   0   0   0   0   1  13  64   0   0   0   0   2   0   0   0  26   8]
 [  0   0   0   0   0   0   0   0 110   0   0   0   0   0   4   0   0   0]
 [  1   0   0   0   0   0   0   0   0 108   4   2   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   1 213   0   0   0   4   0   0   0]
 [  4   2   0   1   0   0   0   0   7   7   0 198   0   0   0   0   0   0]
 [  0   0   0   0   7   0   2   5   0   0   0   0  63   5   0   1  25   7]
 [  1   0   7   0   0   2   0   2   0   0   0   0   3 184   0   2  10   7]
 [  7   0   1   0   0   0   0   0   5   0   1   0   0   0 198   0   0   0]
 [  0   4   0   0   0   0   0   0   0   0   0   6   0   1   0 118   0   0]
 [  0   0   0   0   1   0   3   8   1   0   0   0   3   0   0   1  96   1]
 [  0   0   0   2   0   0   3   0   0   0   0   2   0   0   0   2   1 208]]
Accuracy: 0.8833333333333333
```

In [ ]:
```
from sklearn.metrics import classification_report
print(classification_report(encoded_y_test,y_pred_classes))
```

```
              precision    recall  f1-score   support

           0       0.93      0.89      0.91       219
           1       0.92      0.74      0.82       113
           2       0.88      0.93      0.90       117
           3       0.92      0.98      0.95       213
           4       0.93      0.86      0.89       115
           5       0.96      0.86      0.91       217
           6       0.91      0.95      0.93       220
           7       0.81      0.56      0.66       114
           8       0.72      0.96      0.82       114
           9       0.89      0.94      0.92       115
          10       0.97      0.98      0.97       218
          11       0.84      0.90      0.87       219
          12       0.88      0.55      0.67       115
          13       0.95      0.84      0.90       218
          14       0.95      0.93      0.94       212
          15       0.93      0.91      0.92       129
          16       0.57      0.84      0.68       114
          17       0.85      0.95      0.90       218

    accuracy                           0.88      3000
   macro avg       0.88      0.87      0.87      3000
weighted avg       0.89      0.88      0.88      3000
```

In [ ]:

```
from sklearn.metrics import precision_recall_fscore_support
res = []
for l in range(18):
     prec,recall,_,_ = precision_recall_fscore_support(np.array(encoded_y_test)==l,
                                                       np.array(y_pred_classes)==l,
                                                       pos_label=True,average=None)
     res.append([l,recall[0],recall[1]])

pd.DataFrame(res,columns = ['class','specificity','sensitivity'])
```

Out[ ]:

	class	specificity	sensitivity
0	0	0.994966	0.885845
1	1	0.997575	0.743363
2	2	0.994797	0.931624
3	3	0.993541	0.981221
4	4	0.997227	0.860870
5	5	0.997485	0.857143
6	6	0.992446	0.950000
7	7	0.994802	0.561404
8	8	0.985100	0.964912
9	9	0.995494	0.939130
10	10	0.997484	0.977064
11	11	0.986695	0.904110
12	12	0.996880	0.547826
13	13	0.996765	0.844037
14	14	0.996055	0.933962
15	15	0.996865	0.914729
16	16	0.975398	0.842105
17	17	0.987060	0.954128