

Voice Emotion Classification

Import Modules

```
In [5]: #importing the library
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import librosa
import librosa.display
from IPython.display import Audio
import warnings
warnings.filterwarnings('ignore')
```

Load the DataSet

```
In [6]: #loading the dataset
paths = []
labels = []
import os
for dirname, _, filenames in os.walk('input'):
    for filename in filenames:
        paths.append(os.path.join(dirname, filename))

        label = filename.split('_')[-1]

        label = label.split('.')[0]
        labels.append(label.lower())

print("Dataset Loaded")
```

Dataset Loaded

```
In [8]: #check labels of the dataset
labels[:5]
```

```
Out[8]: ['fear', 'fear', 'fear', 'fear', 'fear']
```

```
In [9]: #check dataset
df = pd.DataFrame()
df['speech'] = paths
df['label'] = labels
df.head()
```

```
Out[9]:
```

	speech	label
0	/kaggle/input/toronto-emotional-speech-set-tes...	fear
1	/kaggle/input/toronto-emotional-speech-set-tes...	fear
2	/kaggle/input/toronto-emotional-speech-set-tes...	fear
3	/kaggle/input/toronto-emotional-speech-set-tes...	fear
4	/kaggle/input/toronto-emotional-speech-set-tes...	fear

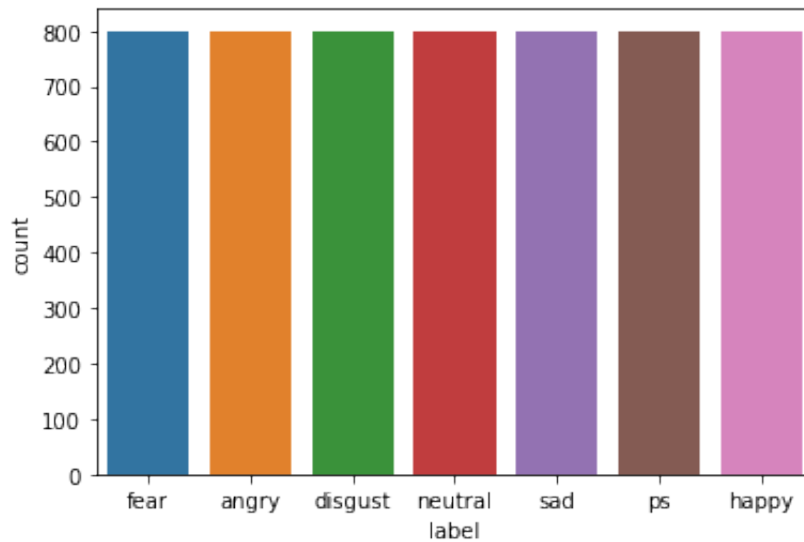
```
In [10]: #count the value label
df['label'].value_counts()
```

```
Out[10]: fear      800
angry      800
disgust    800
neutral    800
sad        800
ps         800
happy      800
Name: label, dtype: int64
```

Exploratory Data Analysis

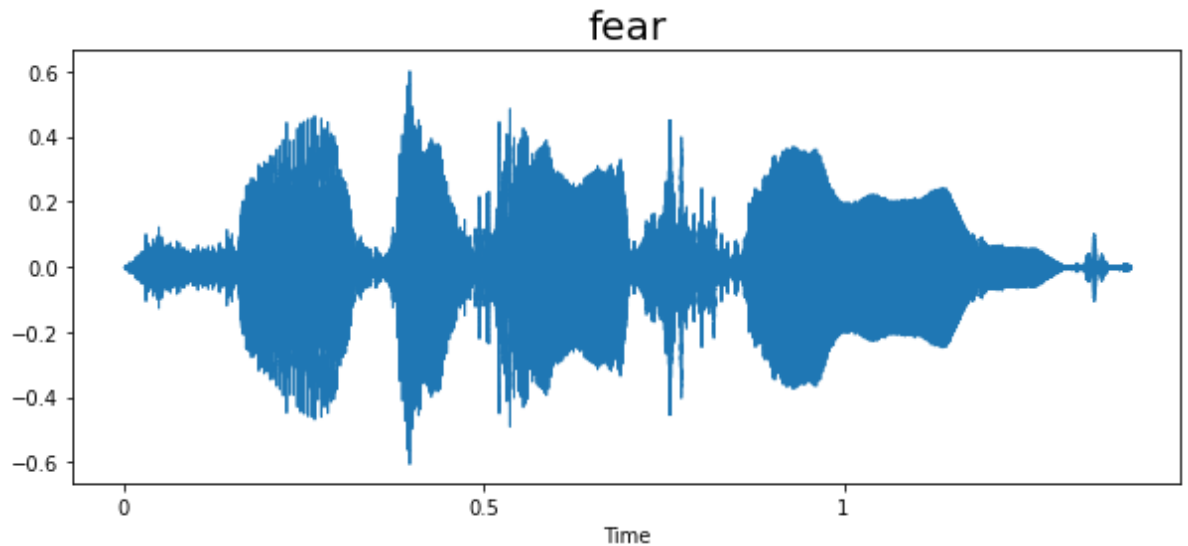
```
In [11]: #count the value label  
sns.countplot(df['label'])
```

```
Out[11]: <AxesSubplot:xlabel='label', ylabel='count'>
```



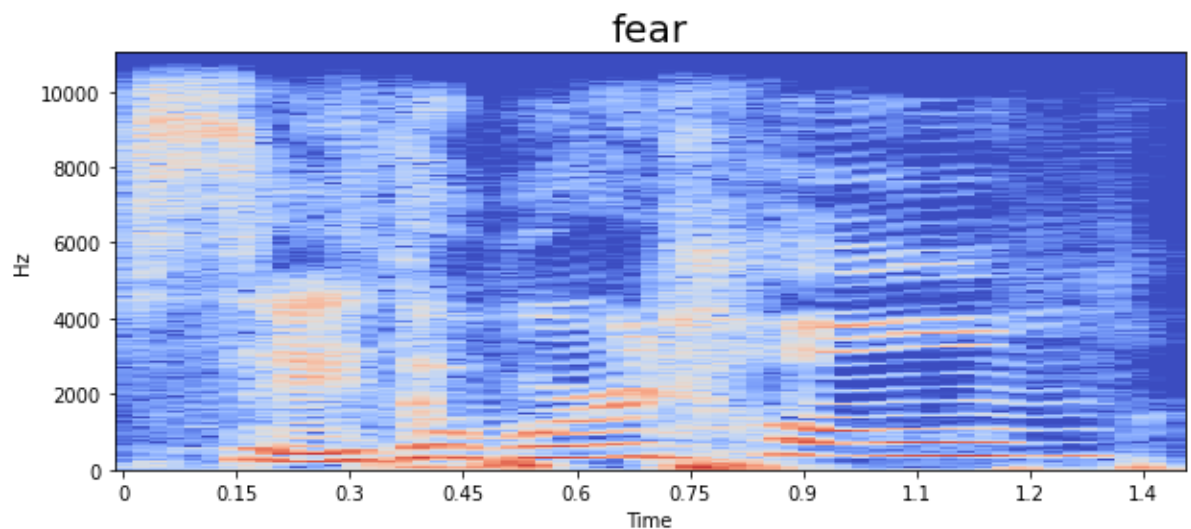
```
In [12]: #plot waveplot  
def waveplot(data, sr, emotion):  
    plt.figure(figsize = (10, 4))  
    plt.title(emotion, size= 20)  
    librosa.display.waveshow(data, sr=sr)  
    plt.show()  
  
def spectrogram(data, sr, emotion):  
    x = librosa.stft(data)  
    xdb = librosa.amplitude_to_db(abs(x))  
    plt.figure(figsize = (10, 4))  
    plt.title(emotion, size= 20)  
    librosa.display.specshow(xdb, sr=sr, x_axis='time', y_axis='hz')
```

```
In [13]: #plot for fear
emotion = 'fear'
path = np.array(df['speech'][df['label']==emotion])[0]
data, sampling_rate = librosa.load(path)
waveplot(data, sampling_rate, emotion)
spectrogram(data, sampling_rate, emotion)
Audio(path)
```

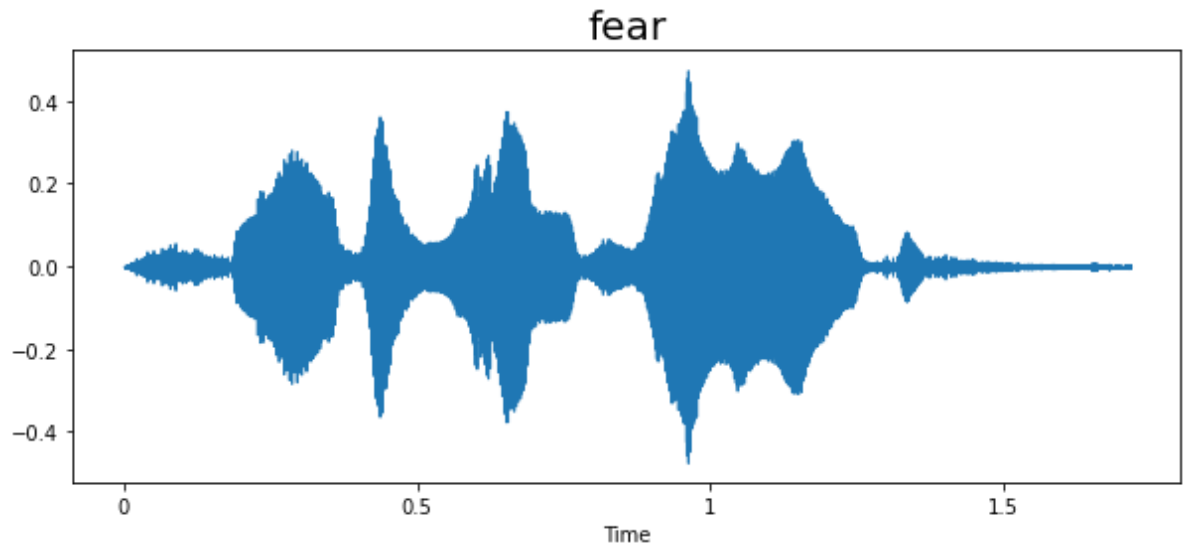


Out[13]:

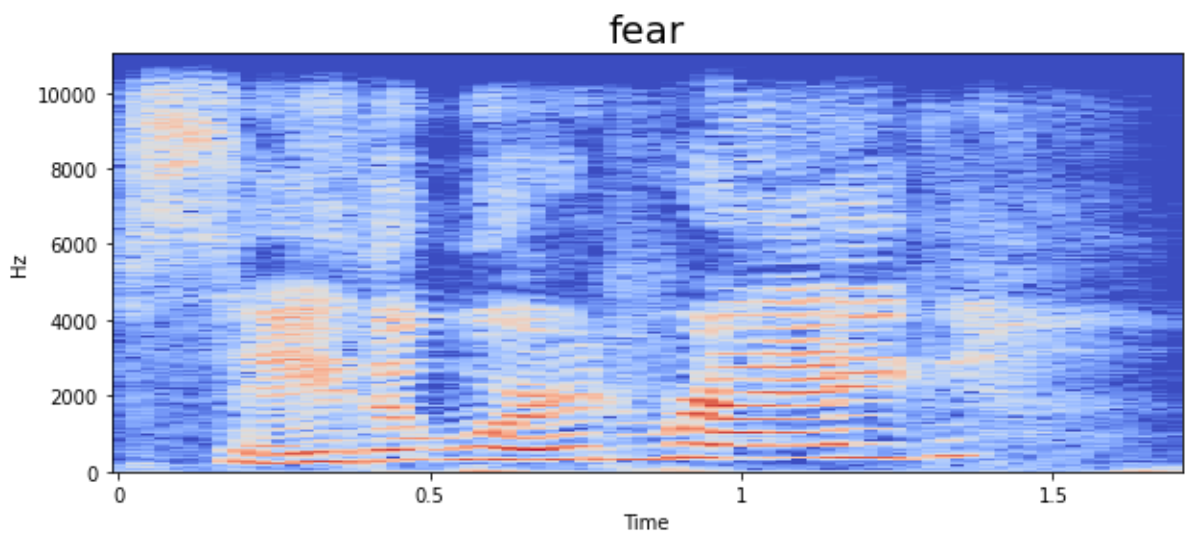
-00:00



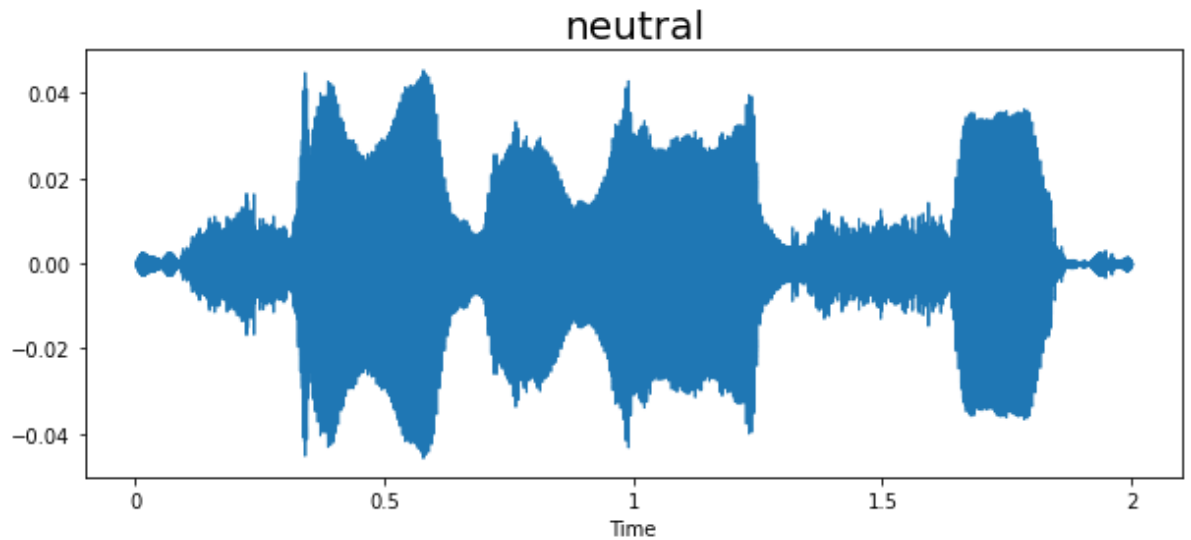
```
In [30]: emotion = 'fear'
path = np.array(df['speech'][df['label']==emotion])[10]
data, sampling_rate = librosa.load(path)
waveplot(data, sampling_rate, emotion)
spectrogram(data, sampling_rate, emotion)
Audio(path)
```



Out [30]: -00:00

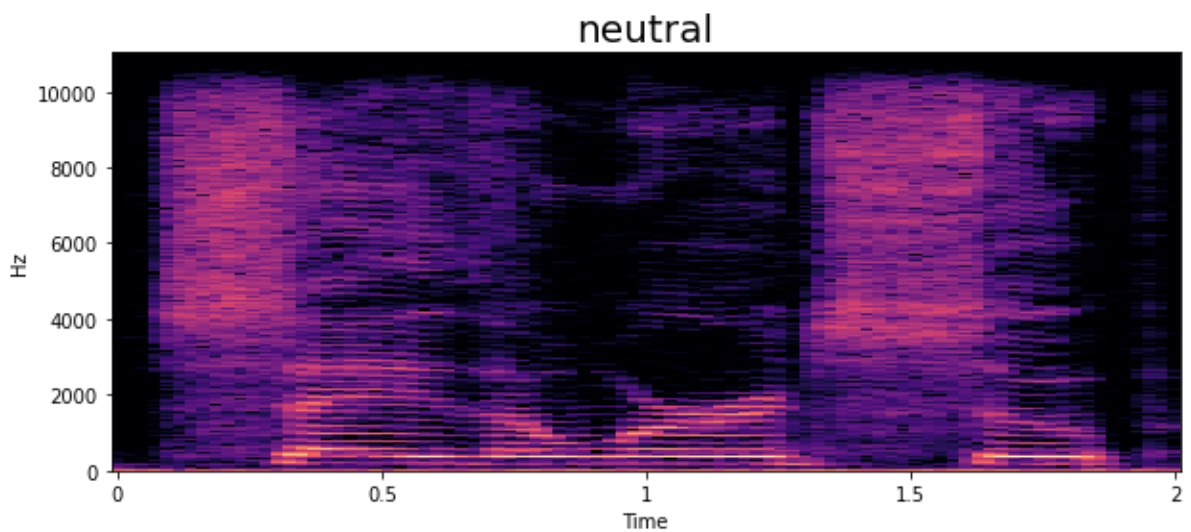


```
In [14]: #plot neutral
emotion = 'neutral'
path = np.array(df['speech'][df['label']==emotion])[0]
data, sampling_rate = librosa.load(path)
waveplot(data, sampling_rate, emotion)
spectrogram(data, sampling_rate, emotion)
Audio(path)
```



Out [14]:

-00:00



Feature Extraction

In [15]:

```
def extract_mfcc(filename):
    y, sr = librosa.load(filename, duration=3, offset=0.5)
    mfcc=np.mean(librosa.feature.mfcc(y=y, sr = sr, n_mfcc=40).T, a
    return mfcc
```

In [16]: extract_mfcc(df['speech'][0])

```
Out[16]: array([-287.13037,  87.756935, -4.139177,  24.081968, ...,
                -16.696724,  12.970632,  10.522444, -1.1463214, ...,
                -0.73337686,  12.855532, -19.147291, -6.418063, ...,
                 4.9657683, -2.6571155, -10.655444,  4.9578815, ...,
                -14.55586,  15.37587,  18.444935,  23.878317, ...,
                 31.495146,  17.326372, -4.7648373,  1.7432437, ...,
                -12.009847,  7.34574, -3.2051265, -7.171453, ...,
                -11.410634, -2.001994, -5.610964,  4.5321946, ...,
                -11.396625, -8.892363, -3.7391376,  4.8819685, ...,
                -1.5599903,  2.465447,  11.59915,  11.042192 ]

dtype=float32)
```

In [17]: x_mfcc = df['speech'].apply(lambda x: extract_mfcc(x))

In [18]: x_mfcc

```
Out[18]: 0      [-287.13037, 87.756935, -4.139177, 24.081968, ...
1      [-350.0836, 37.654167, -6.2928553, 17.09615, 4...
2      [-341.78152, 56.153652, -16.617884, 23.219698, ...
3      [-309.17456, 24.854897, -8.00109, 10.065497, -...
4      [-347.12918, 49.69155, -27.524876, 22.730288, ...

...
5595    [-376.5839, 63.9598, -3.0598662, 11.498796, -2...
5596    [-316.5801, 43.54606, -9.336959, -0.198444, -5...
5597    [-359.7638, 81.01536, -18.355762, 5.3012295, -...
5598    [-354.38315, 103.432144, -15.916284, -10.30884...
5599    [-391.15958, 56.44471, -1.0464002, 0.9587419, ...
Name: speech, Length: 5600, dtype: object
```

```
In [19]: X= [x for x in x_mfcc]
X = np.array(X)
X.shape
```

Out[19]: (5600, 40)

```
In [20]: X = np.expand_dims(X, -1)  
X.shape
```

```
Out[20]: (5600, 40, 1)
```

```
In [21]: from sklearn.preprocessing import OneHotEncoder  
enc = OneHotEncoder()  
y = enc.fit_transform(df[['label']])
```

```
In [22]: y = y.toarray()
```

```
In [23]: y.shape
```

```
Out[23]: (5600, 7)
```

Create a LSTM model


```
In [24]: from keras.models import Sequential
from keras.layers import Dense, LSTM, Dropout

model = Sequential([
    LSTM(123, return_sequences = False, input_shape=(40, 1)),
    Dense(64, activation='relu'),
    Dropout(0.2),
    Dense(32, activation = 'relu'),
    Dropout(0.2),
    Dense(7, activation='softmax'),
])

model.compile(loss = "categorical_crossentropy", optimizer = 'adam')
model.summary()
```

Model: "sequential_1"

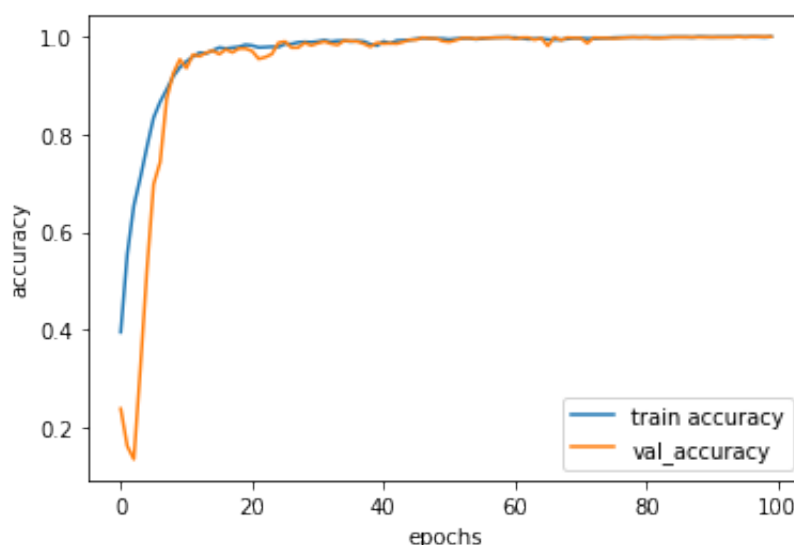
Layer (type)	Output Shape	Param #
=====		
lstm_1 (LSTM)	(None, 123)	61500
dense_3 (Dense)	(None, 64)	7936
dropout_2 (Dropout)	(None, 64)	0
dense_4 (Dense)	(None, 32)	2080
dropout_3 (Dropout)	(None, 32)	0
dense_5 (Dense)	(None, 7)	231
=====		
Total params: 71,747		
Trainable params: 71,747		
Non-trainable params: 0		

```
In [25]: #train the model
history=model.fit(X, y, validation_split=0.2, epochs=100, batch_size=32)

Epoch 10/100
9/9 [=====] - 0s 11ms/step - loss: 0.2081
- accuracy: 0.9371 - val_loss: 0.2065 - val_accuracy: 0.9536
Epoch 11/100
9/9 [=====] - 0s 11ms/step - loss: 0.1764
- accuracy: 0.9491 - val_loss: 0.2161 - val_accuracy: 0.9357
Epoch 12/100
9/9 [=====] - 0s 12ms/step - loss: 0.1429
- accuracy: 0.9594 - val_loss: 0.1331 - val_accuracy: 0.9634
Epoch 13/100
9/9 [=====] - 0s 11ms/step - loss: 0.1240
- accuracy: 0.9672 - val_loss: 0.1376 - val_accuracy: 0.9598
Epoch 14/100
9/9 [=====] - 0s 12ms/step - loss: 0.1127
- accuracy: 0.9658 - val_loss: 0.1165 - val_accuracy: 0.9670
Epoch 15/100
9/9 [=====] - 0s 10ms/step - loss: 0.1023
- accuracy: 0.9717 - val_loss: 0.0911 - val_accuracy: 0.9714
Epoch 16/100
9/9 [=====] - 0s 10ms/step - loss: 0.0860
```

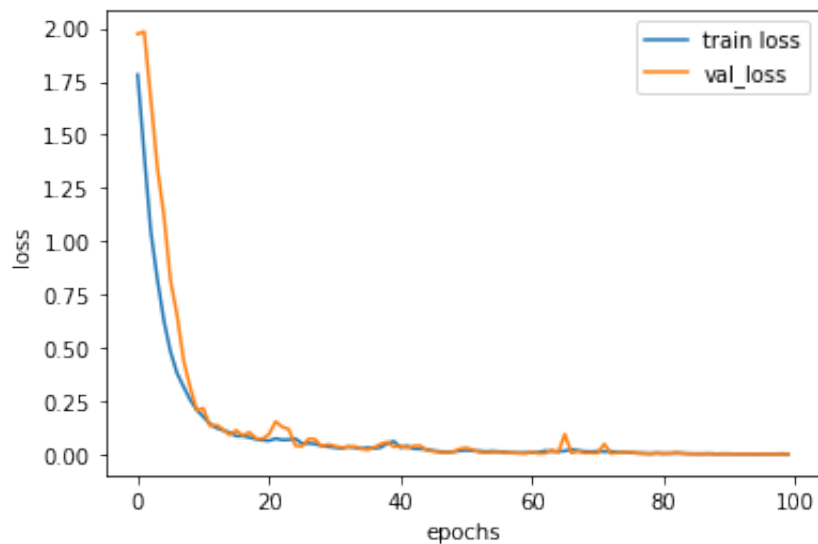
```
In [26]: epochs = list(range(100))
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

plt.plot(epochs, acc, label = 'train accuracy')
plt.plot(epochs, val_acc, label = 'val_accuracy')
plt.xlabel('epochs')
plt.ylabel('accuracy')
plt.legend()
plt.show()
```



```
In [27]: epochs = list(range(100))
loss = history.history['loss']
val_loss = history.history['val_loss']

plt.plot(epochs, loss, label = 'train loss')
plt.plot(epochs, val_loss, label = 'val_loss')
plt.xlabel('epochs')
plt.ylabel('loss')
plt.legend()
plt.show()
```



```
In [ ]:
```