## Music Genre Classification with GTZAN Dataset

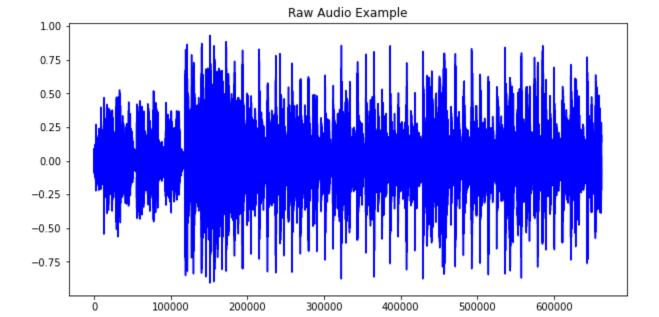
#### Audio Files | Mel Spectrograms | CSV with extracted features

In this Project we learn basic information about audio data, which are needed for using audio in Machine Learning and Deep Learning models.

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Corizo Internship

#### **Import Libraries**

```
In [3]:
        # imoprt libraries
        import pandas as pd
        import numpy as np
        import seaborn as sns
        import matplotlib.pyplot as plt
        %matplotlib inline
        from glob import glob # allows us to list all files to a directory
        import IPython
        import IPython.display as ipd # to play the Audio Files
        import librosa # main package for working with Audio Data
        import librosa.display
        # Make a list of all the way files in the dataset and store them in a variable
In [4]:
        audio_files = glob("/kaggle/input/gtzan-dataset-music-genre-classification/Data/genres_o
In [5]: # Play the first Audio file
        ipd.Audio(audio_files[0])
Out[5]:
            0:00 / 0:30
In [6]: # load the audio file and show raw data and sample rate
        y, sr = librosa.load(audio_files[0])
        print("Y is a numpy array:", y)
        print("Shape of Y:", y.shape)
        print("Sample Rate:", sr)
        Y is a numpy array: [-0.0196228 -0.00567627 0.00927734 ... 0.01547241 0.01220703
          0.0319519 ]
        Shape of Y: (661794,)
        Sample Rate: 22050
In [7]: # turn raw data array to pd series and plot the audio example
        pd.Series(y).plot(figsize=(10,5), title="Raw Audio Example", color='blue');
```

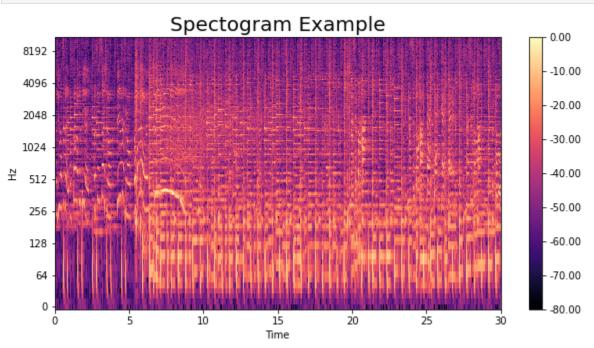


```
In [8]: # Use STFT on raw audio data
D = librosa.stft(y)
# convert from aplitude to decibel values by taking the absolute value of D in reference
S_db = librosa.amplitude_to_db(np.abs(D), ref=np.max)
# see the shape of transformed data
print("New shape of transformed data", S_db.shape)
```

New shape of transformed data (1025, 1293)

#### Plotting Audio File as a Spectogram

```
In [9]: # plot transformed data as spectogram
fig, ax = plt.subplots(figsize=(10,5))
img = librosa.display.specshow(S_db, x_axis='time', y_axis='log', ax=ax)
ax.set_title('Spectogram Example', fontsize=20)
fig.colorbar(img, ax=ax, format=f'%0.2f');
```



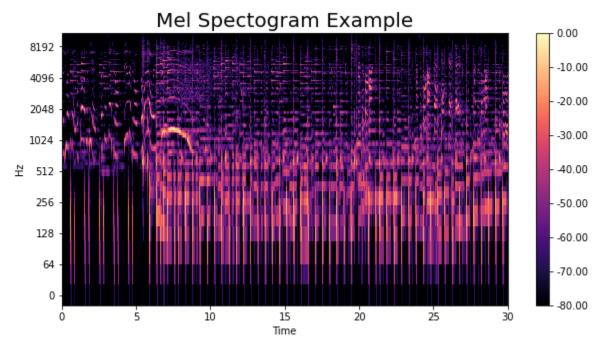
```
# use that converting function as above
S_db_mel = librosa.amplitude_to_db(S, ref=np.max)
```

Shape of Mel Spectogram (256, 1293)

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:2: FutureWarning: Pass y=[-0.0196228 -0.00567627 0.00927734 ... 0.01547241 0.01220703
```

0.0319519 ] as keyword args. From version 0.10 passing these as positional arguments w ill result in an error

```
In [11]: # plot the mel spectogram
fig, ax = plt.subplots(figsize=(10,5))
img = librosa.display.specshow(S_db_mel, x_axis='time', y_axis='log', ax=ax)
ax.set_title('Mel Spectogram Example', fontsize=20)
fig.colorbar(img, ax=ax, format=f'%0.2f');
```



#### EDA - Exploratory Data Analysis

In [12]: # load csv file
df = pd.read\_csv("/kaggle/input/gtzan-dataset-music-genre-classification/Data/features\_3

In [13]: df.head() # first 5 entries

t[13]:		filename	length	chroma_stft_mean	chroma_stft_var	rms_mean	rms_var	spectral_centroid_mean
	0	blues.00000.0.wav	66149	0.335406	0.091048	0.130405	0.003521	1773.065032
	1	blues.00000.1.wav	66149	0.343065	0.086147	0.112699	0.001450	1816.693777
	2	blues.00000.2.wav	66149	0.346815	0.092243	0.132003	0.004620	1788.539719
	3	blues.00000.3.wav	66149	0.363639	0.086856	0.132565	0.002448	1655.289045
	4	blues.00000.4.way	66149	0.335579	0.088129	0.143289	0.001701	1630.656199

5 rows × 60 columns

```
In [14]: df.shape # see the shape of df
```

Out[14]: (9990, 60)

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<pre><class 'pandas.core.frame.dataframe'=""> PangaIndova 0000 ontring 0 to 0000</class></pre>							
	RangeIndex: 9990 entries, 0 to 9989  Data columns (total 60 columns):						
#	Column	Non-Null Count	Dtype				
 0	filename	9990 non-null	object				
1	length	9990 non-null	int64				
2	chroma_stft_mean	9990 non-null	float64				
3	chroma_stft_var	9990 non-null	float64				
4	rms_mean	9990 non-null	float64				
5	rms_var	9990 non-null	float64				
6	spectral_centroid_mean	9990 non-null	float64				
7	spectral_centroid_var	9990 non-null	float64				
8	spectral_bandwidth_mean	9990 non-null	float64				
9	spectral_bandwidth_var	9990 non-null	float64				
10	rolloff_mean	9990 non-null	float64				
11	rolloff_var	9990 non-null	float64				
12	zero_crossing_rate_mean	9990 non-null	float64				
13	zero_crossing_rate_var	9990 non-null 9990 non-null	float64				
14 15	harmony_mean harmony_var	9990 non-null	float64 float64				
16	perceptr_mean	9990 non-null	float64				
17	perceptr_var	9990 non-null	float64				
18	tempo	9990 non-null	float64				
19	mfcc1_mean	9990 non-null	float64				
20	mfcc1_var	9990 non-null	float64				
21	mfcc2_mean	9990 non-null	float64				
22	mfcc2_var	9990 non-null	float64				
23	mfcc3_mean	9990 non-null	float64				
24	mfcc3_var	9990 non-null	float64				
25	mfcc4_mean	9990 non-null	float64				
26	mfcc4_var	9990 non-null	float64				
27	mfcc5_mean	9990 non-null	float64				
28	mfcc5_var	9990 non-null	float64				
29	mfcc6_mean	9990 non-null	float64				
30 31	mfcc6_var mfcc7_mean	9990 non-null 9990 non-null	float64 float64				
32	mfcc7_mean	9990 non-null	float64				
33	mfcc8_mean	9990 non-null	float64				
34	mfcc8_var	9990 non-null	float64				
35	mfcc9_mean	9990 non-null	float64				
36	mfcc9_var	9990 non-null	float64				
37	mfcc10_mean	9990 non-null	float64				
38	mfcc10_var	9990 non-null	float64				
39	mfcc11_mean	9990 non-null	float64				
40	mfcc11_var	9990 non-null	float64				
41	mfcc12_mean	9990 non-null	float64				
42	mfcc12_var	9990 non-null	float64				
43	mfcc13_mean	9990 non-null	float64				
44 45	mfcc13_var mfcc14_mean	9990 non-null 9990 non-null	float64 float64				
46	mfcc14_mean	9990 non-null	float64				
47	mfcc15_mean	9990 non-null	float64				
48	mfcc15_var	9990 non-null	float64				
49	mfcc16_mean	9990 non-null	float64				
50	mfcc16_var	9990 non-null	float64				
51	mfcc17_mean	9990 non-null	float64				
52	mfcc17_var	9990 non-null	float64				
53	mfcc18_mean	9990 non-null	float64				
54	mfcc18_var	9990 non-null	float64				
55	mfcc19_mean	9990 non-null	float64				
56	mfcc19_var	9990 non-null	float64				
57	mfcc20_mean	9990 non-null	float64				
Loading [Math Jay]/jay/out	_mfcc20_var put/CommonHTML/fonts/TeX/fontdata.j	9990 non-null	float64				
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59 label 9990 non-null object

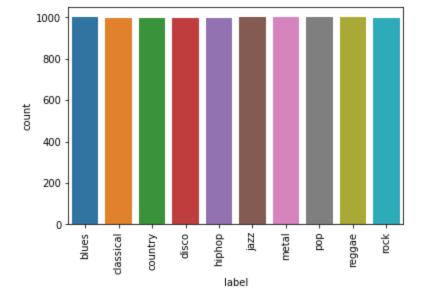
dtypes: float64(57), int64(1), object(2)

memory usage: 4.6+ MB

In [16]: df.isnull().sum() # checking for missing values

	filename	0
Out[16]:	length	0
	chroma_stft_mean	0
	chroma_stft_var	0
	rms_mean	0
	rms_var	0
	spectral_centroid_mean	0
	spectral_centroid_var	0
	spectral_bandwidth_mean	0
	spectral_bandwidth_var	0
	rolloff_mean	0
	rolloff_var	0
	zero_crossing_rate_mean	0
	zero_crossing_rate_var	0
	harmony_mean	0
	harmony_var	0 0
	perceptr_mean perceptr_var	0
	tempo	0
	mfcc1_mean	0
	mfcc1_war	0
	mfcc2_mean	0
	mfcc2_var	0
	mfcc3_mean	0
	mfcc3_var	0
	mfcc4_mean	0
	mfcc4_var	0
	mfcc5_mean	0
	mfcc5_var	0
	mfcc6_mean	0
	mfcc6_var	0
	mfcc7_mean	0
	mfcc7_var	0
	mfcc8_mean	0
	mfcc8_var	0
	mfcc9_mean	0
	mfcc9_var mfcc10_mean	0 0
	mfcc10_war	0
	mfcc10_var mfcc11_mean	0
	mfcc11_var	0
	mfcc12_mean	0
	mfcc12_var	0
	mfcc13_mean	0
	mfcc13_var	0
	mfcc14_mean	0
	mfcc14_var	0
	mfcc15_mean	0
	mfcc15_var	0
	mfcc16_mean	0
	mfcc16_var	0
	mfcc17_mean	0
	mfcc17_var	0
	mfcc18_mean	0
	mfcc18_var mfcc19_mean	0
	mfcc19_mean mfcc19_var	0 0
	mfcc20_mean	0
	mfcc20_war	0
	label	0
	dtype: int64	J
	11	// 7

In [17]: sns.countplot(x=df.label) # plot the categories plt.xticks(rotation=90);
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# **Data Preprocessing**

```
In [18]: # drop filename column and show new df first 5 entries
    df = df.drop(labels='filename', axis=1)
    df.head()
```

Out[18]:		length	chroma_stft_mean	chroma_stft_var	rms_mean	rms_var	spectral_centroid_mean	spectral_centroid_v
	0	66149	0.335406	0.091048	0.130405	0.003521	1773.065032	167541.6308
	1	66149	0.343065	0.086147	0.112699	0.001450	1816.693777	90525.6908
	2	66149	0.346815	0.092243	0.132003	0.004620	1788.539719	111407.4376
	3	66149	0.363639	0.086856	0.132565	0.002448	1655.289045	111952.2845
	4	66149	0.335579	0.088129	0.143289	0.001701	1630.656199	79667.2676

5 rows × 59 columns

```
In [20]: # import labelencoder and scaler
    from sklearn.preprocessing import LabelEncoder
    from sklearn.preprocessing import StandardScaler
    encoder = LabelEncoder()
    scaler = StandardScaler()
```

```
In [21]: data = df.iloc[:, :-1] # get the other columns
   data
```

]:		length	chroma_stft_mean	chroma_stft_var	rms_mean	rms_var	spectral_centroid_mean	spectral_centro
	0	66149	0.335406	0.091048	0.130405	0.003521	1773.065032	167541.6
	1	66149	0.343065	0.086147	0.112699	0.001450	1816.693777	90525.€
	2	66149	0.346815	0.092243	0.132003	0.004620	1788.539719	111407.4
	3	66149	0.363639	0.086856	0.132565	0.002448	1655.289045	111952.2
	4	66149	0.335579	0.088129	0.143289	0.001701	1630.656199	79667.2
	9985	66149	0.349126	0.080515	0.050019	0.000097	1499.083005	164266.8
	9986	66149	0.372564	0.082626	0.057897	0.000088	1847.965128	281054.9
	9987	66149	0.347481	0.089019	0.052403	0.000701	1346.157659	662956.2
	9988	66149	0.387527	0.084815	0.066430	0.000320	2084.515327	203891.0
	9989	66149	0.369293	0.086759	0.050524	0.000067	1634.330126	411429.1

9990 rows × 58 columns

In [22]: labels = df.iloc[:, -1] # get labels column

Out[21]

```
labels.to_frame()
                label
Out[22]:
              0 blues
              1 blues
              2 blues
              3 blues
```

4 blues ... 9985 rock 9986 rock 9987 rock 9988 rock 9989

9990 rows × 1 columns

rock

# Getting x and y ready

```
In [23]: # assign x and y, scale x and encode y
         x = np.array(data, dtype = float)
         x = scaler.fit_transform(data)
         y = encoder.fit_transform(labels)
         x.shape, y.shape
         ((9990, 58), (9990,))
Out[23]:
In [24]: # split data to train and test data
         from sklearn.model_selection import train_test_split
```

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```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.33)
x_train.shape, x_test.shape, y_train.shape, y_test.shape

Out[24]: ((6693, 58), (3297, 58), (6693,), (3297,))
```

### Modelling using CNN

In [29]: # compile model

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```
In [26]: # import deep learning libraries
         import tensorflow as tf
         from tensorflow import keras
         from keras.models import Sequential
         # build model
In [27]:
         model = keras.models.Sequential([
             keras.layers.Dense(512, activation="relu", input_shape=(x_train.shape[1],)),
             keras.layers.Dropout(0.2),
             keras.layers.Dense(256, activation="relu"),
             keras.layers.Dropout(0.2),
             keras.layers.Dense(128, activation="relu"),
             keras.layers.Dropout(0.2),
             keras.layers.Dense(64,activation="relu"),
             keras.layers.Dropout(0.2),
             keras.layers.Dense(10, activation="softmax"),
         ])
         2023-01-31 03:10:22.818886: I tensorflow/core/common_runtime/process_util.cc:146] Creati
         ng new thread pool with default inter op setting: 2. Tune using inter_op_parallelism_thr
         eads for best performance.
In [28]:
         print(model.summary()) # show summary of model
         Model: "sequential"
                                     Output Shape
                                                               Param #
         Layer (type)
                                                               ========
                                                               30208
         dense (Dense)
                                     (None, 512)
         dropout (Dropout)
                                     (None, 512)
         dense_1 (Dense)
                                     (None, 256)
                                                               131328
         dropout_1 (Dropout)
                                     (None, 256)
         dense_2 (Dense)
                                     (None, 128)
                                                               32896
         dropout_2 (Dropout)
                                     (None, 128)
         dense_3 (Dense)
                                                               8256
                                     (None, 64)
         dropout_3 (Dropout)
                                     (None, 64)
                                                               0
         dense_4 (Dense)
                                     (None, 10)
         ______
         Total params: 203,338
         Trainable params: 203,338
         Non-trainable params: 0
         None
```

model\_compile(ontimizer='adam' loss='sparse\_categorical\_crossentropy', metrics='accuracy

In [30]: # fit model - training
history = model.fit(x\_train, y\_train, validation\_data=(x\_test, y\_test), epochs=300, batc

2023-01-31 03:12:53.715391: I tensorflow/compiler/mlir/mlir\_graph\_optimization\_pass.cc:1
85] None of the MLIR Optimization Passes are enabled (registered 2)

```
Epoch 1/300
- val_loss: 1.1452 - val_accuracy: 0.5936
Epoch 2/300
- val_loss: 0.8906 - val_accuracy: 0.6991
Epoch 3/300
val_loss: 0.7619 - val_accuracy: 0.7413
Epoch 4/300
val_loss: 0.7118 - val_accuracy: 0.7631
Epoch 5/300
val_loss: 0.6379 - val_accuracy: 0.7880
Epoch 6/300
val_loss: 0.5899 - val_accuracy: 0.8077
Epoch 7/300
- val_loss: 0.5615 - val_accuracy: 0.8156
Epoch 8/300
val_loss: 0.5401 - val_accuracy: 0.8262
Epoch 9/300
val_loss: 0.5000 - val_accuracy: 0.8329
Epoch 10/300
val_loss: 0.4826 - val_accuracy: 0.8474
Epoch 11/300
- val_loss: 0.4419 - val_accuracy: 0.8568
Epoch 12/300
- val_loss: 0.4543 - val_accuracy: 0.8584
Epoch 13/300
- val_loss: 0.4290 - val_accuracy: 0.8702
- val_loss: 0.4403 - val_accuracy: 0.8653
Epoch 15/300
- val_loss: 0.4412 - val_accuracy: 0.8693
Epoch 16/300
- val_loss: 0.4184 - val_accuracy: 0.8747
Epoch 17/300
- val_loss: 0.3948 - val_accuracy: 0.8844
Epoch 18/300
- val_loss: 0.3905 - val_accuracy: 0.8829
Epoch 19/300
- val_loss: 0.3941 - val_accuracy: 0.8850
Epoch 20/300
- val_loss: 0.4027 - val_accuracy: 0.8844
Epoch 21/300
- val_loss: 0.3826 - val_accuracy: 0.8878
```

Fnoch 22/300

```
- val_loss: 0.3872 - val_accuracy: 0.8890
Epoch 23/300
- val_loss: 0.3648 - val_accuracy: 0.8966
Epoch 24/300
- val_loss: 0.3745 - val_accuracy: 0.8966
- val_loss: 0.4155 - val_accuracy: 0.8829
Epoch 26/300
- val_loss: 0.3728 - val_accuracy: 0.8972
Epoch 27/300
53/53 [============== ] - 0s 9ms/step - loss: 0.1393 - accuracy: 0.9535 -
val_loss: 0.3655 - val_accuracy: 0.8972
Epoch 28/300
val_loss: 0.3920 - val_accuracy: 0.8944
Epoch 29/300
- val_loss: 0.3866 - val_accuracy: 0.9026
Epoch 30/300
- val_loss: 0.3969 - val_accuracy: 0.8996
Epoch 31/300
- val_loss: 0.4086 - val_accuracy: 0.8969
Epoch 32/300
- val_loss: 0.3967 - val_accuracy: 0.8957
Epoch 33/300
- val_loss: 0.3933 - val_accuracy: 0.8984
Epoch 34/300
- val_loss: 0.4340 - val_accuracy: 0.8902
Epoch 35/300
- val_loss: 0.4161 - val_accuracy: 0.8972
Epoch 36/300
- val_loss: 0.4168 - val_accuracy: 0.9014
- val_loss: 0.4103 - val_accuracy: 0.9005
Epoch 38/300
- val_loss: 0.4347 - val_accuracy: 0.8987
Epoch 39/300
- val_loss: 0.4174 - val_accuracy: 0.9032
Epoch 40/300
- val_loss: 0.4161 - val_accuracy: 0.9014
Epoch 41/300
- val_loss: 0.3964 - val_accuracy: 0.9039
Epoch 42/300
- val_loss: 0.3821 - val_accuracy: 0.9090
Epoch 43/300
```

```
val_loss: 0.4286 - val_accuracy: 0.9045
Epoch 44/300
- val_loss: 0.4190 - val_accuracy: 0.9020
Epoch 45/300
- val_loss: 0.4284 - val_accuracy: 0.9014
Epoch 46/300
- val_loss: 0.4105 - val_accuracy: 0.9045
Epoch 47/300
- val_loss: 0.4048 - val_accuracy: 0.9035
Epoch 48/300
- val_loss: 0.4160 - val_accuracy: 0.9063
Epoch 49/300
- val_loss: 0.4226 - val_accuracy: 0.9035
Epoch 50/300
- val_loss: 0.3937 - val_accuracy: 0.9054
Epoch 51/300
- val_loss: 0.4041 - val_accuracy: 0.9039
Epoch 52/300
- val_loss: 0.4148 - val_accuracy: 0.9075
Epoch 53/300
- val_loss: 0.4331 - val_accuracy: 0.9069
Epoch 54/300
- val_loss: 0.4235 - val_accuracy: 0.9054
- val_loss: 0.4032 - val_accuracy: 0.9075
Epoch 56/300
- val_loss: 0.4030 - val_accuracy: 0.9099
Epoch 57/300
- val_loss: 0.4250 - val_accuracy: 0.9032
Epoch 58/300
- val_loss: 0.4056 - val_accuracy: 0.9142
Epoch 59/300
- val_loss: 0.4259 - val_accuracy: 0.9093
Epoch 60/300
- val_loss: 0.4439 - val_accuracy: 0.9069
Epoch 61/300
- val_loss: 0.4246 - val_accuracy: 0.9087
Epoch 62/300
- val_loss: 0.4188 - val_accuracy: 0.9093
- val_loss: 0.4142 - val_accuracy: 0.9011
Epoch 64/300
```

<u>- val loss: 0.4083 - val accura</u>cy: 0.9090

```
Epoch 65/300
- val_loss: 0.4539 - val_accuracy: 0.9096
Epoch 66/300
- val_loss: 0.4243 - val_accuracy: 0.9099
Epoch 67/300
- val_loss: 0.3933 - val_accuracy: 0.9178
Epoch 68/300
- val_loss: 0.3997 - val_accuracy: 0.9142
Epoch 69/300
- val_loss: 0.4446 - val_accuracy: 0.9090
Epoch 70/300
- val_loss: 0.4338 - val_accuracy: 0.9111
Epoch 71/300
- val_loss: 0.4352 - val_accuracy: 0.9093
Epoch 72/300
- val_loss: 0.4290 - val_accuracy: 0.9093
Epoch 73/300
- val_loss: 0.4406 - val_accuracy: 0.9042
Epoch 74/300
- val_loss: 0.4392 - val_accuracy: 0.9066
Epoch 75/300
- val_loss: 0.4003 - val_accuracy: 0.9120
Epoch 76/300
- val_loss: 0.4145 - val_accuracy: 0.9069
Epoch 77/300
- val_loss: 0.4104 - val_accuracy: 0.9123
- val_loss: 0.4131 - val_accuracy: 0.9139
Epoch 79/300
- val_loss: 0.4685 - val_accuracy: 0.9090
Epoch 80/300
- val_loss: 0.4381 - val_accuracy: 0.9099
Epoch 81/300
- val_loss: 0.4081 - val_accuracy: 0.9145
Epoch 82/300
- val_loss: 0.4475 - val_accuracy: 0.9133
Epoch 83/300
- val_loss: 0.4636 - val_accuracy: 0.9105
Epoch 84/300
- val_loss: 0.4248 - val_accuracy: 0.9078
Epoch 85/300
- val_loss: 0.4510 - val_accuracy: 0.9054
```

Fnoch 86/300

```
- val_loss: 0.4595 - val_accuracy: 0.9051
Epoch 87/300
- val_loss: 0.4338 - val_accuracy: 0.9075
Epoch 88/300
- val_loss: 0.4375 - val_accuracy: 0.9126
- val_loss: 0.4510 - val_accuracy: 0.9123
Epoch 90/300
53/53 [============== ] - 0s 9ms/step - loss: 0.0390 - accuracy: 0.9891 -
val_loss: 0.4391 - val_accuracy: 0.9136
Epoch 91/300
- val_loss: 0.4478 - val_accuracy: 0.9102
Epoch 92/300
- val_loss: 0.4939 - val_accuracy: 0.9105
Epoch 93/300
- val_loss: 0.4523 - val_accuracy: 0.9084
Epoch 94/300
- val_loss: 0.4328 - val_accuracy: 0.9123
Epoch 95/300
- val_loss: 0.4547 - val_accuracy: 0.9163
Epoch 96/300
- val_loss: 0.4291 - val_accuracy: 0.9148
Epoch 97/300
- val_loss: 0.4206 - val_accuracy: 0.9178
Epoch 98/300
- val_loss: 0.4578 - val_accuracy: 0.9066
Epoch 99/300
- val_loss: 0.4244 - val_accuracy: 0.9120
Epoch 100/300
- val_loss: 0.4567 - val_accuracy: 0.9126
- val_loss: 0.4544 - val_accuracy: 0.9133
Epoch 102/300
- val_loss: 0.4163 - val_accuracy: 0.9154
Epoch 103/300
- val_loss: 0.4488 - val_accuracy: 0.9123
Epoch 104/300
val_loss: 0.4591 - val_accuracy: 0.9133
Epoch 105/300
- val_loss: 0.4706 - val_accuracy: 0.9111
Epoch 106/300
- val_loss: 0.4545 - val_accuracy: 0.9178
Epoch 107/300
```

```
val_loss: 0.4368 - val_accuracy: 0.9178
Epoch 108/300
- val_loss: 0.4555 - val_accuracy: 0.9148
Epoch 109/300
- val_loss: 0.4564 - val_accuracy: 0.9187
Epoch 110/300
- val_loss: 0.4371 - val_accuracy: 0.9166
Epoch 111/300
- val_loss: 0.4495 - val_accuracy: 0.9130
Epoch 112/300
- val_loss: 0.4710 - val_accuracy: 0.9142
Epoch 113/300
val_loss: 0.4552 - val_accuracy: 0.9133
Epoch 114/300
- val_loss: 0.4196 - val_accuracy: 0.9126
Epoch 115/300
- val_loss: 0.4829 - val_accuracy: 0.9126
Epoch 116/300
val_loss: 0.4795 - val_accuracy: 0.9120
Epoch 117/300
val_loss: 0.4832 - val_accuracy: 0.9145
Epoch 118/300
val_loss: 0.4547 - val_accuracy: 0.9084
- val_loss: 0.4951 - val_accuracy: 0.9084
Epoch 120/300
- val_loss: 0.4540 - val_accuracy: 0.9151
Epoch 121/300
- val_loss: 0.4392 - val_accuracy: 0.9166
Epoch 122/300
- val_loss: 0.4691 - val_accuracy: 0.9126
Epoch 123/300
- val_loss: 0.4816 - val_accuracy: 0.9081
Epoch 124/300
val_loss: 0.4356 - val_accuracy: 0.9130
Epoch 125/300
- val_loss: 0.4497 - val_accuracy: 0.9130
Epoch 126/300
- val_loss: 0.4807 - val_accuracy: 0.9139
- val_loss: 0.4556 - val_accuracy: 0.9148
Epoch 128/300
```

- val loss: 0.4487 - val accuracy: 0.9163 Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js

```
Epoch 129/300
- val_loss: 0.4410 - val_accuracy: 0.9184
Epoch 130/300
val_loss: 0.4665 - val_accuracy: 0.9136
Epoch 131/300
- val_loss: 0.4478 - val_accuracy: 0.9166
Epoch 132/300
- val_loss: 0.4296 - val_accuracy: 0.9151
Epoch 133/300
- val_loss: 0.4386 - val_accuracy: 0.9148
Epoch 134/300
- val_loss: 0.4626 - val_accuracy: 0.9154
Epoch 135/300
- val_loss: 0.4956 - val_accuracy: 0.9108
Epoch 136/300
- val_loss: 0.4743 - val_accuracy: 0.9111
Epoch 137/300
- val_loss: 0.4737 - val_accuracy: 0.9123
Epoch 138/300
- val_loss: 0.4763 - val_accuracy: 0.9160
Epoch 139/300
- val_loss: 0.4643 - val_accuracy: 0.9142
Epoch 140/300
- val_loss: 0.4717 - val_accuracy: 0.9142
Epoch 141/300
- val_loss: 0.4520 - val_accuracy: 0.9175
Epoch 142/300
53/53 [============== ] - 0s 9ms/step - loss: 0.0254 - accuracy: 0.9925 -
val_loss: 0.4511 - val_accuracy: 0.9160
Epoch 143/300
53/53 [============== ] - 0s 9ms/step - loss: 0.0178 - accuracy: 0.9954 -
val_loss: 0.4693 - val_accuracy: 0.9178
Epoch 144/300
val_loss: 0.4773 - val_accuracy: 0.9120
Epoch 145/300
val_loss: 0.5029 - val_accuracy: 0.9142
Epoch 146/300
- val_loss: 0.4370 - val_accuracy: 0.9181
Epoch 147/300
- val_loss: 0.4316 - val_accuracy: 0.9190
Epoch 148/300
- val_loss: 0.4752 - val_accuracy: 0.9102
Epoch 149/300
- val_loss: 0.4866 - val_accuracy: 0.9181
```

```
- val_loss: 0.4792 - val_accuracy: 0.9193
Epoch 151/300
- val_loss: 0.4737 - val_accuracy: 0.9154
Epoch 152/300
val_loss: 0.4919 - val_accuracy: 0.9151
Epoch 153/300
- val_loss: 0.5237 - val_accuracy: 0.9133
Epoch 154/300
53/53 [============== - - 1s 9ms/step - loss: 0.0411 - accuracy: 0.9891 -
val_loss: 0.4692 - val_accuracy: 0.9145
Epoch 155/300
53/53 [============== ] - 0s 9ms/step - loss: 0.0207 - accuracy: 0.9933 -
val_loss: 0.4724 - val_accuracy: 0.9120
Epoch 156/300
val_loss: 0.4744 - val_accuracy: 0.9221
Epoch 157/300
- val_loss: 0.4763 - val_accuracy: 0.9202
Epoch 158/300
val_loss: 0.4658 - val_accuracy: 0.9148
Epoch 159/300
- val_loss: 0.4711 - val_accuracy: 0.9105
Epoch 160/300
- val_loss: 0.4949 - val_accuracy: 0.9154
Epoch 161/300
- val_loss: 0.4939 - val_accuracy: 0.9105
Epoch 162/300
- val_loss: 0.4935 - val_accuracy: 0.9154
Epoch 163/300
- val_loss: 0.4747 - val_accuracy: 0.9190
Epoch 164/300
- val_loss: 0.5223 - val_accuracy: 0.9081
- val_loss: 0.4798 - val_accuracy: 0.9154
Epoch 166/300
- val_loss: 0.4878 - val_accuracy: 0.9142
Epoch 167/300
val_loss: 0.5138 - val_accuracy: 0.9126
Epoch 168/300
val_loss: 0.5229 - val_accuracy: 0.9120
Epoch 169/300
- val_loss: 0.4875 - val_accuracy: 0.9166
Epoch 170/300
- val_loss: 0.4625 - val_accuracy: 0.9178
Epoch 171/300
```

```
- val_loss: 0.4601 - val_accuracy: 0.9205
Epoch 172/300
- val_loss: 0.4763 - val_accuracy: 0.9145
Epoch 173/300
- val_loss: 0.4849 - val_accuracy: 0.9157
Epoch 174/300
- val_loss: 0.5338 - val_accuracy: 0.9175
Epoch 175/300
val_loss: 0.4956 - val_accuracy: 0.9184
Epoch 176/300
- val_loss: 0.5129 - val_accuracy: 0.9154
Epoch 177/300
- val_loss: 0.5188 - val_accuracy: 0.9163
Epoch 178/300
- val_loss: 0.5752 - val_accuracy: 0.9136
Epoch 179/300
- val_loss: 0.5342 - val_accuracy: 0.9184
Epoch 180/300
- val_loss: 0.5903 - val_accuracy: 0.9126
Epoch 181/300
- val_loss: 0.6376 - val_accuracy: 0.9069
Epoch 182/300
- val_loss: 0.6046 - val_accuracy: 0.9087
- val_loss: 0.5091 - val_accuracy: 0.9111
Epoch 184/300
- val_loss: 0.5427 - val_accuracy: 0.9087
Epoch 185/300
- val_loss: 0.5423 - val_accuracy: 0.9096
Epoch 186/300
- val_loss: 0.4941 - val_accuracy: 0.9151
Epoch 187/300
- val_loss: 0.5218 - val_accuracy: 0.9130
Epoch 188/300
- val_loss: 0.5391 - val_accuracy: 0.9084
Epoch 189/300
- val_loss: 0.4868 - val_accuracy: 0.9190
Epoch 190/300
- val_loss: 0.4987 - val_accuracy: 0.9190
- val_loss: 0.4861 - val_accuracy: 0.9175
Epoch 192/300
```

- val loss: 0.4815 - val accuracy: 0.9224 Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js

```
Epoch 193/300
- val_loss: 0.4798 - val_accuracy: 0.9242
Epoch 194/300
- val_loss: 0.5569 - val_accuracy: 0.9130
Epoch 195/300
- val_loss: 0.4919 - val_accuracy: 0.9166
Epoch 196/300
- val_loss: 0.4625 - val_accuracy: 0.9199
Epoch 197/300
- val_loss: 0.4842 - val_accuracy: 0.9199
Epoch 198/300
- val_loss: 0.4925 - val_accuracy: 0.9187
Epoch 199/300
- val_loss: 0.4695 - val_accuracy: 0.9199
Epoch 200/300
- val_loss: 0.5453 - val_accuracy: 0.9120
Epoch 201/300
- val_loss: 0.4736 - val_accuracy: 0.9184
Epoch 202/300
- val_loss: 0.5300 - val_accuracy: 0.9151
Epoch 203/300
- val_loss: 0.5292 - val_accuracy: 0.9181
Epoch 204/300
- val_loss: 0.4898 - val_accuracy: 0.9166
Epoch 205/300
- val_loss: 0.5086 - val_accuracy: 0.9114
Epoch 206/300
- val_loss: 0.5632 - val_accuracy: 0.9087
Epoch 207/300
- val_loss: 0.5517 - val_accuracy: 0.9075
Epoch 208/300
- val_loss: 0.4850 - val_accuracy: 0.9181
Epoch 209/300
- val_loss: 0.5003 - val_accuracy: 0.9175
Epoch 210/300
- val_loss: 0.5173 - val_accuracy: 0.9199
Epoch 211/300
- val_loss: 0.5476 - val_accuracy: 0.9139
Epoch 212/300
- val_loss: 0.5697 - val_accuracy: 0.9120
Epoch 213/300
- val_loss: 0.5444 - val_accuracy: 0.9096
```

Fnoch 214/300

```
- val_loss: 0.5621 - val_accuracy: 0.9114
Epoch 215/300
- val_loss: 0.5416 - val_accuracy: 0.9120
Epoch 216/300
- val_loss: 0.5414 - val_accuracy: 0.9169
Epoch 217/300
val_loss: 0.5109 - val_accuracy: 0.9166
Epoch 218/300
- val_loss: 0.5386 - val_accuracy: 0.9120
Epoch 219/300
- val_loss: 0.4591 - val_accuracy: 0.9190
Epoch 220/300
- val_loss: 0.5132 - val_accuracy: 0.9178
Epoch 221/300
- val_loss: 0.5377 - val_accuracy: 0.9181
Epoch 222/300
- val_loss: 0.5775 - val_accuracy: 0.9202
Epoch 223/300
- val_loss: 0.5079 - val_accuracy: 0.9169
Epoch 224/300
- val_loss: 0.5244 - val_accuracy: 0.9166
Epoch 225/300
- val_loss: 0.4812 - val_accuracy: 0.9208
Epoch 226/300
- val_loss: 0.5477 - val_accuracy: 0.9136
Epoch 227/300
- val_loss: 0.4890 - val_accuracy: 0.9196
Epoch 228/300
- val_loss: 0.4899 - val_accuracy: 0.9227
- val_loss: 0.4936 - val_accuracy: 0.9196
Epoch 230/300
- val_loss: 0.5391 - val_accuracy: 0.9175
Epoch 231/300
- val_loss: 0.4980 - val_accuracy: 0.9187
Epoch 232/300
- val_loss: 0.4917 - val_accuracy: 0.9217
Epoch 233/300
- val_loss: 0.5386 - val_accuracy: 0.9178
Epoch 234/300
- val_loss: 0.5928 - val_accuracy: 0.9148
Epoch 235/300
```

```
- val_loss: 0.5288 - val_accuracy: 0.9136
Epoch 236/300
- val_loss: 0.5163 - val_accuracy: 0.9175
Epoch 237/300
- val_loss: 0.5052 - val_accuracy: 0.9190
Epoch 238/300
- val_loss: 0.5157 - val_accuracy: 0.9172
Epoch 239/300
- val_loss: 0.4995 - val_accuracy: 0.9178
Epoch 240/300
- val_loss: 0.4890 - val_accuracy: 0.9193
Epoch 241/300
- val_loss: 0.5080 - val_accuracy: 0.9214
Epoch 242/300
- val_loss: 0.4694 - val_accuracy: 0.9281
Epoch 243/300
- val_loss: 0.5065 - val_accuracy: 0.9221
Epoch 244/300
- val_loss: 0.5159 - val_accuracy: 0.9221
Epoch 245/300
- val_loss: 0.5528 - val_accuracy: 0.9208
Epoch 246/300
- val_loss: 0.5107 - val_accuracy: 0.9184
- val_loss: 0.5133 - val_accuracy: 0.9202
Epoch 248/300
- val_loss: 0.4911 - val_accuracy: 0.9224
Epoch 249/300
- val_loss: 0.5075 - val_accuracy: 0.9239
Epoch 250/300
- val_loss: 0.5568 - val_accuracy: 0.9211
Epoch 251/300
- val_loss: 0.5629 - val_accuracy: 0.9202
Epoch 252/300
- val_loss: 0.5568 - val_accuracy: 0.9211
Epoch 253/300
- val_loss: 0.5554 - val_accuracy: 0.9178
Epoch 254/300
- val_loss: 0.5396 - val_accuracy: 0.9233
Epoch 255/300
- val_loss: 0.5257 - val_accuracy: 0.9227
Epoch 256/300
```

- val loss: 0.5110 - val accuracy: 0.9260 Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js

```
Epoch 257/300
- val_loss: 0.5562 - val_accuracy: 0.9224
Epoch 258/300
val_loss: 0.4884 - val_accuracy: 0.9196
Epoch 259/300
- val_loss: 0.5115 - val_accuracy: 0.9251
Epoch 260/300
val_loss: 0.5243 - val_accuracy: 0.9263
Epoch 261/300
- val_loss: 0.5064 - val_accuracy: 0.9272
Epoch 262/300
- val_loss: 0.5415 - val_accuracy: 0.9214
Epoch 263/300
- val_loss: 0.5164 - val_accuracy: 0.9178
Epoch 264/300
- val_loss: 0.5326 - val_accuracy: 0.9208
Epoch 265/300
- val_loss: 0.5726 - val_accuracy: 0.9178
Epoch 266/300
- val_loss: 0.5448 - val_accuracy: 0.9139
Epoch 267/300
- val_loss: 0.4932 - val_accuracy: 0.9257
Epoch 268/300
- val_loss: 0.5150 - val_accuracy: 0.9236
Epoch 269/300
- val_loss: 0.5103 - val_accuracy: 0.9214
Epoch 270/300
- val_loss: 0.5431 - val_accuracy: 0.9175
Epoch 271/300
- val_loss: 0.5383 - val_accuracy: 0.9224
Epoch 272/300
- val_loss: 0.5677 - val_accuracy: 0.9199
Epoch 273/300
- val_loss: 0.5685 - val_accuracy: 0.9211
Epoch 274/300
- val_loss: 0.5475 - val_accuracy: 0.9199
Epoch 275/300
- val_loss: 0.5287 - val_accuracy: 0.9151
Epoch 276/300
- val_loss: 0.4886 - val_accuracy: 0.9205
Epoch 277/300
- val_loss: 0.4961 - val_accuracy: 0.9251
```

Fnoch 278/300

```
- val_loss: 0.5380 - val_accuracy: 0.9221
Epoch 279/300
- val_loss: 0.5303 - val_accuracy: 0.9242
Epoch 280/300
- val_loss: 0.5437 - val_accuracy: 0.9190
- val_loss: 0.5139 - val_accuracy: 0.9236
Epoch 282/300
- val_loss: 0.5235 - val_accuracy: 0.9196
Epoch 283/300
- val_loss: 0.5365 - val_accuracy: 0.9160
Epoch 284/300
- val_loss: 0.5367 - val_accuracy: 0.9227
Epoch 285/300
- val_loss: 0.5280 - val_accuracy: 0.9145
Epoch 286/300
val_loss: 0.5003 - val_accuracy: 0.9199
Epoch 287/300
- val_loss: 0.5183 - val_accuracy: 0.9211
Epoch 288/300
- val_loss: 0.5189 - val_accuracy: 0.9154
Epoch 289/300
- val_loss: 0.5438 - val_accuracy: 0.9178
Epoch 290/300
- val_loss: 0.5673 - val_accuracy: 0.9169
Epoch 291/300
- val_loss: 0.5500 - val_accuracy: 0.9175
Epoch 292/300
- val_loss: 0.5710 - val_accuracy: 0.9148
val_loss: 0.5903 - val_accuracy: 0.9169
Epoch 294/300
val_loss: 0.5408 - val_accuracy: 0.9214
Epoch 295/300
val_loss: 0.5788 - val_accuracy: 0.9175
Epoch 296/300
- val_loss: 0.5675 - val_accuracy: 0.9126
Epoch 297/300
- val_loss: 0.5451 - val_accuracy: 0.9178
Epoch 298/300
- val_loss: 0.5591 - val_accuracy: 0.9208
Epoch 299/300
```

```
- val_loss: 0.5208 - val_accuracy: 0.9199
       Epoch 300/300
       val_loss: 0.5440 - val_accuracy: 0.9190
In [31]: # evaluate model
       _, accuracy = model.evaluate(x_test, y_test, batch_size=128)
       In [32]: print("Accuracy:", accuracy) # print accuracy
       Accuracy: 0.9190173149108887
       With Deep Learning we achevied an Accuracy of 92.84%.
In [34]: # Plot results
       pd.DataFrame(history.history).plot(figsize=(12,6))
       plt.show()
       1.75
                                                                    loss
                                                                    accuracy
                                                                    val loss
       1.50
                                                                    val_accuracy
       1.25
       1.00
       0.75
       0.50
       0.25
```

0.00

Ò

50

100

150

200

250