# **Importing Libraries**

```
In [30]:
         import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         import scipy
         import os
         import pickle
         import librosa
         import librosa.display
         from IPython.display import Audio
         from sklearn.model_selection import train_test_split
         from sklearn.preprocessing import LabelEncoder
         import tensorflow as tf
         from tensorflow import keras
```

```
In [31]:
         df = pd.read_csv("/kaggle/input/gtzan-dataset-music-genre-classification/Data/features_3_sec.csv")
         df.head()
```

Out[31]:

	filename	length	chroma_stft_mean	chroma_stft_var	rms_mean	rms_var	spectral_centroid_mean	spectral_centroid_var	spectr
0	blues.00000.0.wav	66149	0.335406	0.091048	0.130405	0.003521	1773.065032	167541.630869	1972.
1	blues.00000.1.wav	66149	0.343065	0.086147	0.112699	0.001450	1816.693777	90525.690866	2010.0
2	blues.00000.2.wav	66149	0.346815	0.092243	0.132003	0.004620	1788.539719	111407.437613	2084.
3	blues.00000.3.wav	66149	0.363639	0.086856	0.132565	0.002448	1655.289045	111952.284517	1960.0
4	blues.00000.4.wav	66149	0.335579	0.088129	0.143289	0.001701	1630.656199	79667.267654	1948.
4					<b>&gt;</b>				

 $5 \text{ rows} \times 60 \text{ columns}$ 

```
In [32]:
          df.shape
Out[32]:
```

(9990, 60)

\_\_notebook\_\_

In [33]:

df.dtypes

\_\_notebook\_\_

Out[33]:

<i>f:</i> 1	-1-44
filename length	object int64
chroma_stft_mean	float64
chroma_stft_var	float64
rms_mean	float64
rms_var	float64
spectral_centroid_mean	float64
spectral_centroid_var	float64
spectral_bandwidth_mean	float64
spectral_bandwidth_var	float64
rolloff_mean	float64
rolloff_var	float64
zero_crossing_rate_mean	float64
zero_crossing_rate_var	float64
harmony_mean	float64
harmony_var	float64
perceptr_mean	float64
perceptr_var	float64
tempo	float64
mfcc1_mean	float64
mfcc1_var	float64
mfcc2_mean	float64
mfcc2_var	float64
mfcc3_mean	float64
mfcc3_var	float64
mfcc4_mean	float64
mfcc4_var	float64
mfcc5_mean	float64
mfcc5_var	float64
mfcc6_mean	float64
mfcc6_var	float64
mfcc7_mean	float64
mfcc7_var	float64 float64
mfcc8_mean mfcc8_var	float64
mfcc9_mean	float64
mfcc9_war	float64
mfcc10_mean	float64
mfcc10_var	float64
mfcc11_mean	float64
mfcc11_var	float64
mfcc12_mean	float64
mfcc12_var	float64
mfcc13_mean	float64
mfcc13_var	float64
mfcc14_mean	float64
mfcc14_var	float64
mfcc15_mean	float64
mfcc15_var	float64
mfcc16_mean	float64
mfcc16_var	float64
mfcc17_mean	float64
mfcc17_var	float64
mfcc18_mean	float64
mfcc18_var	float64
mfcc19_mean	float64
mfcc19_var	float64
mfcc20_mean	float64
mfcc20_var	float64
label	object
dtype: object	

dtype: object

5 rows × 59 columns

# Understanding the audio files

```
In [36]:
         audio_recording="/kaggle/input/gtzan-dataset-music-genre-classification/Data/genres_original/country/country.0
         0050.wav"
         data, sr=librosa.load(audio_recording)
         print(type(data), type(sr))
         <class 'numpy.ndarray'> <class 'int'>
In [37]:
         librosa.load(audio_recording,sr=45600)
Out[37]:
         (array([ 0.04582627, 0.06254332, 0.0583379 , ..., -0.13857861,
                 -0.11823352, -0.05911855], dtype=float32),
          45600)
```

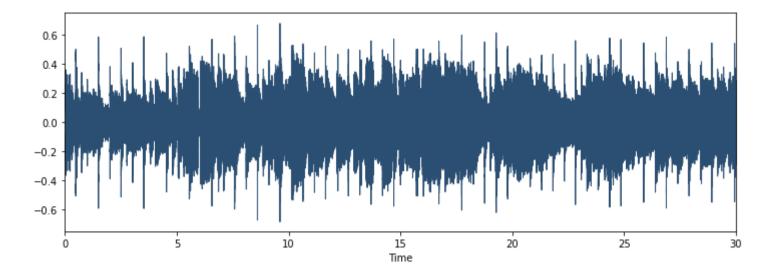
With the help of IPython.display.Audio we can play audio in the notebook. It is a library used for playing the audio in the jupyterlab.

```
In [38]:
         import IPython
         IPython.display.Audio(data,rate=sr)
Out[38]:
              0:00 / 0:30
```

# Visualising audio files

### Plotting Raw wave files

```
In [39]:
         plt.figure(figsize=(12,4))
         librosa.display.waveplot(data,color="#2B4F72")
         plt.show()
```



Waveforms are visual representations of sound as time on the x-axis and amplitude on the y-axis. They are great for allowing us to quickly scan the audio data and visually compare and contrast which genres might be more similar than others.

### Spectrogram

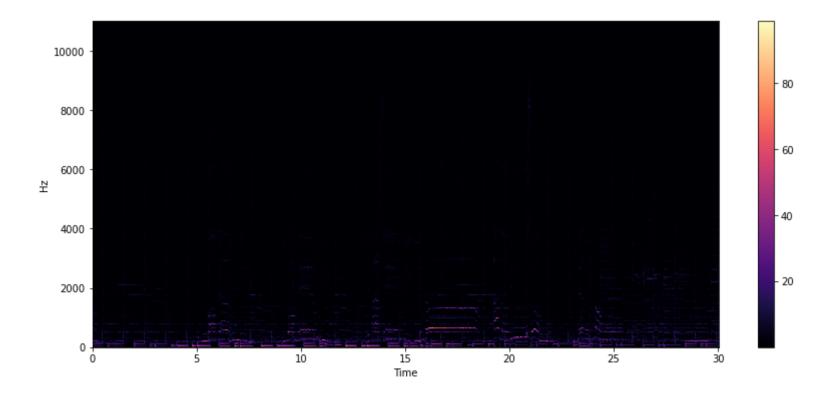
A spectrogram is a visual way of representing the signal loudness of a signal over time at various frequencies present in a particular waveform. Not only can one see whether there is more or less energy at, for example, 2 Hz vs 10 Hz, but one can also see how energy levels vary over time. Spectrograms are sometimes called sonographs, voiceprints, or voicegrams. When the data is represented in a 3D plot, they may be called waterfalls. In 2-dimensional arrays, the first axis is frequency while the second axis is time

```
In [40]:
         stft=librosa.stft(data)
         stft_db=librosa.amplitude_to_db(abs(stft))
         plt.figure(figsize=(14,6))
         librosa.display.specshow(stft, sr=sr, x_axis='time', y_axis='hz')
         plt.colorbar()
```

/opt/conda/lib/python3.7/site-packages/librosa/display.py:955: UserWarning: Trying to display complex-valu ed input. Showing magnitude instead.

"Trying to display complex-valued input. " "Showing magnitude instead."

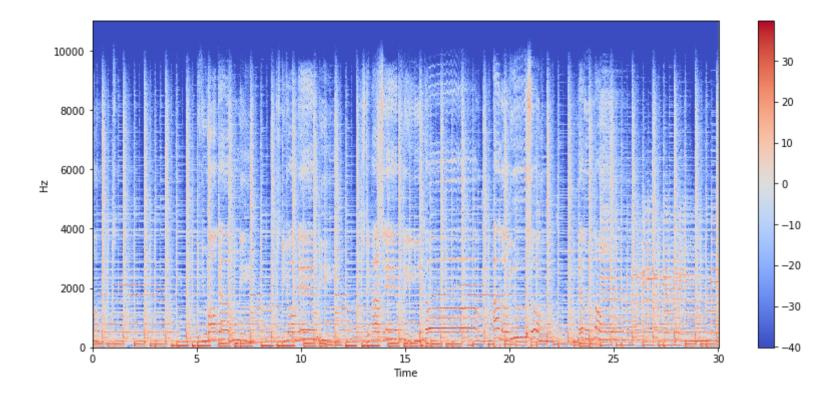
Out[40]: <matplotlib.colorbar.Colorbar at 0x7fa1000f5ad0>



```
In [41]:
         stft=librosa.stft(data)
         stft_db=librosa.amplitude_to_db(abs(stft))
         plt.figure(figsize=(14,6))
         librosa.display.specshow(stft_db,sr=sr,x_axis='time',y_axis='hz')
         plt.colorbar()
```

Out[41]:

<matplotlib.colorbar.Colorbar at 0x7fa100054090>

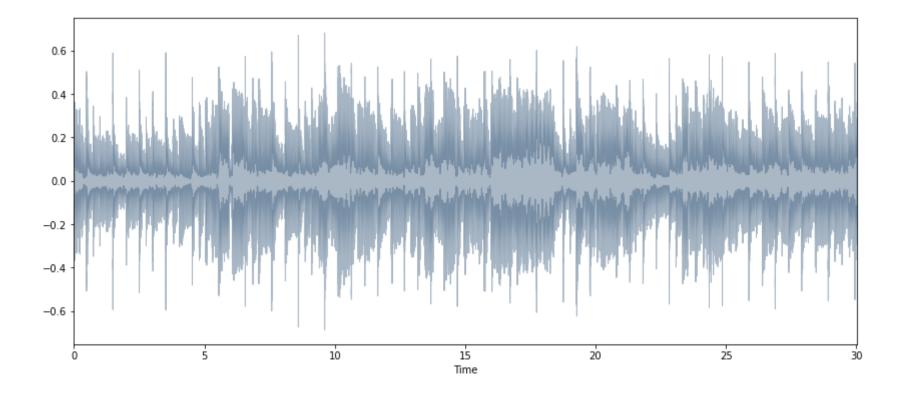


### Spectral Roll-Off

Spectral Rolloff is the frequency below which a specified percentage of the total spectral energy, e.g. 85%, lies librosa.feature.spectral\_rolloff computes the rolloff frequency for each frame in a signal.

```
In [42]:
         spectral_rolloff=librosa.feature.spectral_rolloff(data+0.01, sr=sr)[0]
         plt.figure(figsize=(14,6))
         librosa.display.waveplot(data, sr=sr, alpha=0.4, color="#2B4F72")
Out[42]:
```

<matplotlib.collections.PolyCollection at 0x7fa0e876a190>

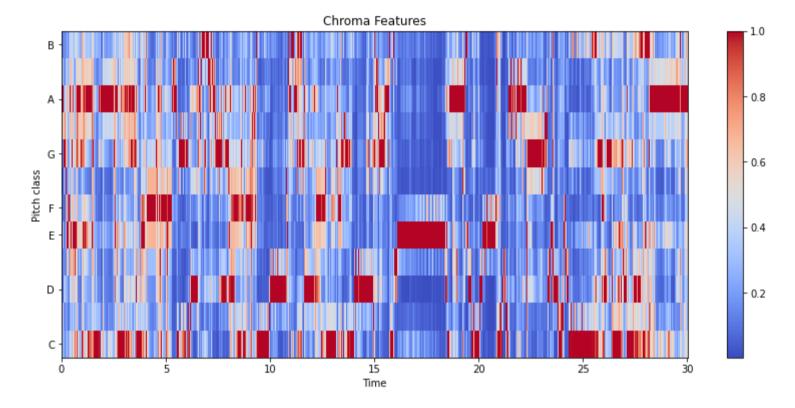


5/16/22, 11:26 AM \_\_notebook\_\_

#### **Chroma Feature**

It is a powerful tool for analyzing music features whose pitches can be meaningfully categorized and whose tuning approximates to the equal-tempered scale. One main property of chroma features is that they capture harmonic and melodic characteristics of music while being robust to changes in timbre and instrumentation

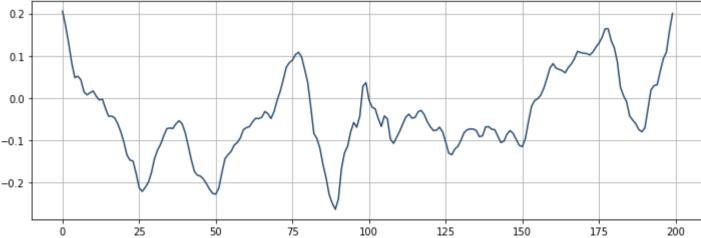
```
In [43]:
         import librosa.display as lplt
         chroma = librosa.feature.chroma_stft(data, sr=sr)
         plt.figure(figsize=(14,6))
         lplt.specshow(chroma, sr=sr, x_axis="time", y_axis="chroma", cmap="coolwarm")
         plt.colorbar()
         plt.title("Chroma Features")
         plt.show()
```



#### **Zero Crossing Rate**

Zero crossing is said to occur if successive samples have different algebraic signs. The rate at which zero-crossings occur is a simple measure of the frequency content of a signal. Zero-crossing rate is a measure of the number of times in a given time interval/frame that the amplitude of the speech signals passes through a value of zero.

```
In [44]:
         start=1000
         end=1200
         plt.figure(figsize=(12,4))
         plt.plot(data[start:end],color="#2B4F72")
         plt.grid()
```



the numbert of zero\_crossings is : 8

```
In [45]:
    zero_cross_rate=librosa.zero_crossings(data[start:end],pad=False)
    print("the numbert of zero_crossings is :", sum(zero_cross_rate))
```

# **Feature Extraction**

Preprocessing of data is required before we finally train the data. We will try and focus on the last column that is 'label' and will encode it with the function LabelEncoder() of sklearn.preprocessing.

```
In [46]:
    class_list=df.iloc[:,-1]
    converter=LabelEncoder()

In [47]:
    y=converter.fit_transform(class_list)
    y

Out[47]:
    array([0, 0, 0, ..., 9, 9, 9])
```

\_\_notebook\_\_

In [48]:

print(df.iloc[:,:-1])

length

```
chroma_stft_mean chroma_stft_var
                                                    rms_mean
                                                               rms_var \
0
       66149
                       0.335406
                                         0.091048
                                                   0.130405 0.003521
1
       66149
                       0.343065
                                         0.086147
                                                   0.112699
                                                              0.001450
2
       66149
                       0.346815
                                         0.092243
                                                   0.132003
                                                              0.004620
3
                                         0.086856
       66149
                       0.363639
                                                   0.132565
                                                              0.002448
4
       66149
                       0.335579
                                         0.088129
                                                   0.143289
                                                              0.001701
                                              . . .
. . .
         . . .
                            . . .
                                                         . . .
9985
       66149
                       0.349126
                                         0.080515
                                                   0.050019
                                                              0.000097
9986
       66149
                       0.372564
                                         0.082626
                                                   0.057897 0.000088
9987
       66149
                       0.347481
                                         0.089019
                                                   0.052403
                                                              0.000701
9988
                       0.387527
       66149
                                         0.084815
                                                   0.066430
                                                              0.000320
9989
       66149
                       0.369293
                                         0.086759 0.050524 0.000067
      spectral_centroid_mean spectral_centroid_var spectral_bandwidth_mean \
0
                  1773.065032
                                        167541.630869
                                                                     1972.744388
1
                                         90525.690866
                                                                     2010.051501
                  1816.693777
2
                  1788.539719
                                        111407.437613
                                                                     2084.565132
3
                  1655.289045
                                        111952.284517
                                                                     1960.039988
                                                                    1948.503884
4
                  1630.656199
                                         79667.267654
. . .
                                                                             . . .
                  1499.083005
9985
                                        164266.886443
                                                                     1718.707215
9986
                  1847.965128
                                        281054.935973
                                                                     1906.468492
9987
                  1346.157659
                                                                     1561.859087
                                        662956.246325
9988
                                                                     2018.366254
                  2084.515327
                                        203891.039161
9989
                  1634.330126
                                        411429.169769
                                                                     1867.422378
      spectral_bandwidth_var
                               rolloff_mean
                                              ... mfcc16_mean
                                                                 mfcc16_var \
0
               117335.771563
                                3714.560359
                                                      -2.853603
                                                                  39.687145
1
                 65671.875673
                                 3869.682242
                                                       4.074709
                                                                   64.748276
2
                                 3997.639160
                 75124.921716
                                                       4.806280
                                                                   67.336563
3
                 82913.639269
                                 3568.300218
                                                      -1.359111
                                                                   47.739452
                 60204.020268
4
                                 3469.992864
                                                                   30.336359
                                                       2.092937
                                         . . .
. . .
                          . . .
                                              . . .
                                                            . . .
9985
                 85931.574523
                                 3015.559458
                                                       5.773784
                                                                  42.485981
9986
                 99727.037054
                                3746.694524
                                                                  32.415203
                                                       2.074155
9987
               138762.841945
                                 2442.362154
                                                                  78.228149
                                                      -1.005473
9988
                 22860.992562
                                 4313.266226
                                                       4.123402
                                                                   28.323744
9989
               119722.211518
                                 3462.042142
                                                       1.342274
                                                                   38.801735
      mfcc17_mean mfcc17_var
                                mfcc18_mean mfcc18_var mfcc19_mean \
0
        -3.241280
                     36.488243
                                    0.722209
                                               38.099152
                                                             -5.050335
1
        -6.055294
                     40.677654
                                    0.159015
                                               51.264091
                                                             -2.837699
                     28.348579
                                               45.717648
                                                             -1.938424
2
        -1.768610
                                    2.378768
                                               34.770935
3
        -3.841155
                     28.337118
                                    1.218588
                                                             -3.580352
                                    1.689446
                                                             -3.392489
4
         0.664582
                     45.880913
                                               51.363583
                                         . . .
9985
        -9.094270
                     38.326839
                                   -4.246976
                                               31.049839
                                                             -5.625813
9986
                     66.418587
                                   -3.081278
                                               54.414265
                                                            -11.960546
       -12.375726
                                               25.980829
9987
        -2.524483
                     21.778994
                                    4.809936
                                                              1.775686
9988
                                    6.462601
        -5.363541
                     17.209942
                                               21.442928
                                                              2.354765
9989
       -11.598399
                     58.983097
                                   -0.178517
                                               55.761299
                                                             -6.903252
                                 mfcc20_var
      mfcc19_var mfcc20_mean
0
       33.618073
                     -0.243027
                                  43.771767
1
       97.030830
                      5.784063
                                  59.943081
2
       53.050835
                      2.517375
                                  33.105122
3
       50.836224
                      3.630866
                                  32.023678
4
       26.738789
                      0.536961
                                  29.146694
9985
       48.804092
                      1.818823
                                  38.966969
9986
                      0.428857
       63.452255
                                  18.697033
                                  41.586990
9987
                     -0.299545
       48.582378
```

```
9988
      24.843613
                     0.675824
                               12.787750
9989
      39.485901
                    -3.412534
                                31.727489
[9990 rows x 58 columns]
```

# Scaling the features

Standard scaler is used to standardize features by removing the mean and scaling to unit variance. The standard score of sample x is calculated as: z = (x - u) / s

```
In [49]:
         from sklearn.preprocessing import StandardScaler
         fit=StandardScaler()
         X=fit.fit_transform(np.array(df.iloc[:,:-1],dtype=float))
```

### **Dividing Training and Testing Dataset**

```
In [50]:
          X_train, X_test, y_train, y_test=train_test_split(X, y, test_size=0.33)
In [51]:
          len(y_test)
Out[51]:
          3297
In [52]:
          len(y_train)
Out[52]:
          6693
```

### **Building the model**

```
In [53]:
         from tensorflow.keras.models import Sequential
In [54]:
         def trainModel(model,epochs,optimizer):
             batch_size=128
             model.compile(optimizer=optimizer,loss='sparse_categorical_crossentropy',metrics='accuracy')
             return model.fit(X_train,y_train,validation_data=(X_test,y_test),epochs=epochs,batch_size=batch_size)
In [55]:
         def plotValidate(history):
             print("Validation Accuracy", max(history.history["val_accuracy"]))
             pd.DataFrame(history.history).plot(figsize=(12,6))
             plt.show()
In [56]:
         import tensorflow as tf
```

```
In [57]:
         model=tf.keras.models.Sequential([
             tf.keras.layers.Dense(512,activation='relu',input_shape=(X_train.shape[1],)),
             tf.keras.layers.Dropout(0.2),
             tf.keras.layers.Dense(256,activation='relu'),
             keras.layers.Dropout(0.2),
             tf.keras.layers.Dense(128,activation='relu'),
             tf.keras.layers.Dropout(0.2),
             tf.keras.layers.Dense(64,activation='relu'),
             tf.keras.layers.Dropout(0.2),
             tf.keras.layers.Dense(10,activation='softmax'),
         ])
         print(model.summary())
         model_history=trainModel(model=model,epochs=600,optimizer='adam')
```

```
Model: "sequential_1"
_____
Layer (type)
        Output Shape
______
      (None, 512)
dense_5 (Dense)
                 30208
_____
dropout_4 (Dropout) (None, 512)
-----
      (None, 256)
dense_6 (Dense)
                131328
dropout_5 (Dropout) (None, 256)
.____
      (None, 128)
dense_7 (Dense)
                 32896
_____
dropout_6 (Dropout)
       (None, 128)
_____
        (None, 64)
dense_8 (Dense)
                 8256
-----
dropout_7 (Dropout) (None, 64)
dense_9 (Dense) (None, 10)
                 650
______
Total params: 203,338
Trainable params: 203,338
Non-trainable params: 0
None
Epoch 1/600
- val_accuracy: 0.6078
Epoch 2/600
- val_accuracy: 0.7106
Epoch 3/600
- val_accuracy: 0.7392
Epoch 4/600
- val_accuracy: 0.7680
Epoch 5/600
- val_accuracy: 0.7892
Epoch 6/600
- val_accuracy: 0.8044
Epoch 7/600
- val_accuracy: 0.8147
Epoch 8/600
- val_accuracy: 0.8356
Epoch 9/600
- val_accuracy: 0.8499
Epoch 10/600
- val_accuracy: 0.8493
Epoch 11/600
- val_accuracy: 0.8532
Epoch 12/600
```

```
- val_accuracy: 0.8626
Epoch 13/600
- val_accuracy: 0.8608
Epoch 14/600
- val_accuracy: 0.8599
Epoch 15/600
- val_accuracy: 0.8717
Epoch 16/600
- val_accuracy: 0.8741
Epoch 17/600
- val_accuracy: 0.8665
Epoch 18/600
- val_accuracy: 0.8684
Epoch 19/600
- val_accuracy: 0.8805
Epoch 20/600
- val_accuracy: 0.8796
Epoch 21/600
- val_accuracy: 0.8872
Epoch 22/600
- val_accuracy: 0.8829
Epoch 23/600
- val_accuracy: 0.8975
Epoch 24/600
- val_accuracy: 0.8917
Epoch 25/600
- val_accuracy: 0.8938
Epoch 26/600
- val_accuracy: 0.8932
Epoch 27/600
- val_accuracy: 0.8926
Epoch 28/600
- val_accuracy: 0.8966
Epoch 29/600
- val_accuracy: 0.8941
Epoch 30/600
- val_accuracy: 0.8975
Epoch 31/600
- val_accuracy: 0.8966
Epoch 32/600
- val_accuracy: 0.8978
Epoch 33/600
```

```
- val_accuracy: 0.8984
Epoch 34/600
- val_accuracy: 0.9026
Epoch 35/600
- val_accuracy: 0.8999
Epoch 36/600
- val_accuracy: 0.8993
Epoch 37/600
- val_accuracy: 0.8944
Epoch 38/600
- val_accuracy: 0.9026
Epoch 39/600
- val_accuracy: 0.9017
Epoch 40/600
- val_accuracy: 0.9011
Epoch 41/600
- val_accuracy: 0.8969
Epoch 42/600
- val_accuracy: 0.9014
Epoch 43/600
- val_accuracy: 0.9057
Epoch 44/600
- val_accuracy: 0.8999
Epoch 45/600
- val_accuracy: 0.8954
Epoch 46/600
- val_accuracy: 0.8999
Epoch 47/600
- val_accuracy: 0.8975
Epoch 48/600
- val_accuracy: 0.8926
Epoch 49/600
- val_accuracy: 0.8996
Epoch 50/600
- val_accuracy: 0.8978
Epoch 51/600
- val_accuracy: 0.8999
Epoch 52/600
- val_accuracy: 0.8975
Epoch 53/600
- val_accuracy: 0.9063
Epoch 54/600
```

```
- val_accuracy: 0.9066
Epoch 55/600
- val_accuracy: 0.9123
Epoch 56/600
- val_accuracy: 0.8990
Epoch 57/600
- val_accuracy: 0.8990
Epoch 58/600
- val_accuracy: 0.9017
Epoch 59/600
- val_accuracy: 0.9039
Epoch 60/600
- val_accuracy: 0.9011
Epoch 61/600
- val_accuracy: 0.9005
Epoch 62/600
- val_accuracy: 0.9078
Epoch 63/600
- val_accuracy: 0.9005
Epoch 64/600
- val_accuracy: 0.9032
Epoch 65/600
- val_accuracy: 0.9078
Epoch 66/600
- val_accuracy: 0.9026
Epoch 67/600
- val_accuracy: 0.9029
Epoch 68/600
- val_accuracy: 0.9029
Epoch 69/600
- val_accuracy: 0.9060
Epoch 70/600
- val_accuracy: 0.9060
Epoch 71/600
- val_accuracy: 0.9029
Epoch 72/600
- val_accuracy: 0.9133
Epoch 73/600
- val_accuracy: 0.9054
Epoch 74/600
- val_accuracy: 0.9051
Epoch 75/600
```

```
- val_accuracy: 0.9075
Epoch 76/600
- val_accuracy: 0.9084
Epoch 77/600
- val_accuracy: 0.8996
Epoch 78/600
- val_accuracy: 0.9130
Epoch 79/600
- val_accuracy: 0.9126
Epoch 80/600
- val_accuracy: 0.9045
Epoch 81/600
- val_accuracy: 0.9108
Epoch 82/600
- val_accuracy: 0.9105
Epoch 83/600
- val_accuracy: 0.9099
Epoch 84/600
- val_accuracy: 0.9029
Epoch 85/600
- val_accuracy: 0.9130
Epoch 86/600
- val_accuracy: 0.9130
Epoch 87/600
- val_accuracy: 0.9111
Epoch 88/600
- val_accuracy: 0.9060
Epoch 89/600
- val_accuracy: 0.9075
Epoch 90/600
- val_accuracy: 0.9054
Epoch 91/600
- val_accuracy: 0.9102
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- val_accuracy: 0.9078
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- val_accuracy: 0.9117
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- val_accuracy: 0.9130
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- val_accuracy: 0.9084
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Epoch 97/600
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Epoch 98/600
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Epoch 99/600
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Epoch 100/600
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Epoch 101/600
- val_accuracy: 0.9060
Epoch 102/600
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Epoch 113/600
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Epoch 115/600
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- val_accuracy: 0.9184
Epoch 117/600
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Epoch 119/600
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Epoch 120/600
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- val_accuracy: 0.9148
Epoch 138/600
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- val_accuracy: 0.9151
Epoch 512/600
- val_accuracy: 0.9145
Epoch 513/600
- val_accuracy: 0.9193
Epoch 514/600
- val_accuracy: 0.9157
Epoch 515/600
- val_accuracy: 0.9224
Epoch 516/600
```

```
- val_accuracy: 0.9172
Epoch 517/600
- val_accuracy: 0.9172
Epoch 518/600
- val_accuracy: 0.9214
Epoch 519/600
- val_accuracy: 0.9190
Epoch 520/600
- val_accuracy: 0.9160
Epoch 521/600
- val_accuracy: 0.9199
Epoch 522/600
- val_accuracy: 0.9242
Epoch 523/600
- val_accuracy: 0.9205
Epoch 524/600
- val_accuracy: 0.9172
Epoch 525/600
- val_accuracy: 0.9221
Epoch 526/600
- val_accuracy: 0.9202
Epoch 527/600
- val_accuracy: 0.9239
Epoch 528/600
- val_accuracy: 0.9214
Epoch 529/600
- val_accuracy: 0.9233
Epoch 530/600
- val_accuracy: 0.9214
Epoch 531/600
- val_accuracy: 0.9175
Epoch 532/600
- val_accuracy: 0.9187
Epoch 533/600
- val_accuracy: 0.9175
Epoch 534/600
- val_accuracy: 0.9163
Epoch 535/600
- val_accuracy: 0.9181
Epoch 536/600
- val_accuracy: 0.9160
Epoch 537/600
```

```
- val_accuracy: 0.9187
Epoch 538/600
- val_accuracy: 0.9166
Epoch 539/600
- val_accuracy: 0.9221
Epoch 540/600
- val_accuracy: 0.9211
Epoch 541/600
- val_accuracy: 0.9205
Epoch 542/600
- val_accuracy: 0.9221
Epoch 543/600
- val_accuracy: 0.9187
Epoch 544/600
- val_accuracy: 0.9181
Epoch 545/600
- val_accuracy: 0.9245
Epoch 546/600
- val_accuracy: 0.9199
Epoch 547/600
- val_accuracy: 0.9254
Epoch 548/600
- val_accuracy: 0.9221
Epoch 549/600
- val_accuracy: 0.9251
Epoch 550/600
- val_accuracy: 0.9205
Epoch 551/600
- val_accuracy: 0.9196
Epoch 552/600
- val_accuracy: 0.9208
Epoch 553/600
- val_accuracy: 0.9227
Epoch 554/600
- val_accuracy: 0.9221
Epoch 555/600
- val_accuracy: 0.9242
Epoch 556/600
- val_accuracy: 0.9193
Epoch 557/600
- val_accuracy: 0.9178
Epoch 558/600
```

```
- val_accuracy: 0.9208
Epoch 559/600
- val_accuracy: 0.9211
Epoch 560/600
- val_accuracy: 0.9224
Epoch 561/600
- val_accuracy: 0.9242
Epoch 562/600
- val_accuracy: 0.9245
Epoch 563/600
- val_accuracy: 0.9248
Epoch 564/600
- val_accuracy: 0.9202
Epoch 565/600
- val_accuracy: 0.9178
Epoch 566/600
- val_accuracy: 0.9199
Epoch 567/600
- val_accuracy: 0.9205
Epoch 568/600
- val_accuracy: 0.9148
Epoch 569/600
- val_accuracy: 0.9175
Epoch 570/600
- val_accuracy: 0.9211
Epoch 571/600
- val_accuracy: 0.9178
Epoch 572/600
- val_accuracy: 0.9221
Epoch 573/600
- val_accuracy: 0.9205
Epoch 574/600
- val_accuracy: 0.9224
Epoch 575/600
- val_accuracy: 0.9202
Epoch 576/600
- val_accuracy: 0.9133
Epoch 577/600
- val_accuracy: 0.9224
Epoch 578/600
- val_accuracy: 0.9175
Epoch 579/600
```

```
- val_accuracy: 0.9181
Epoch 580/600
- val_accuracy: 0.9233
Epoch 581/600
- val_accuracy: 0.9181
Epoch 582/600
- val_accuracy: 0.9157
Epoch 583/600
- val_accuracy: 0.9142
Epoch 584/600
- val_accuracy: 0.9169
Epoch 585/600
- val_accuracy: 0.9178
Epoch 586/600
- val_accuracy: 0.9172
Epoch 587/600
- val_accuracy: 0.9169
Epoch 588/600
- val_accuracy: 0.9178
Epoch 589/600
- val_accuracy: 0.9190
Epoch 590/600
- val_accuracy: 0.9163
Epoch 591/600
- val_accuracy: 0.9196
Epoch 592/600
- val_accuracy: 0.9184
Epoch 593/600
- val_accuracy: 0.9214
Epoch 594/600
- val_accuracy: 0.9178
Epoch 595/600
- val_accuracy: 0.9184
Epoch 596/600
- val_accuracy: 0.9221
Epoch 597/600
- val_accuracy: 0.9184
Epoch 598/600
- val_accuracy: 0.9211
Epoch 599/600
- val_accuracy: 0.9166
Epoch 600/600
```

notebook

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```
- val_accuracy: 0.9160
```

### **Model Evaluation**

```
In [58]:
      test_loss, test_acc=model.evaluate(X_test, y_test, batch_size=128)
      print("The test loss is ",test_loss)
      print("The best accuracy is: ",test_acc*100)
      The test loss is 0.6207043528556824
      The best accuracy is: 91.59842133522034
```

For the CNN model, we had used the Adam optimizer for training the model. The epoch that was chosen for the training model is 600. All of the hidden layers are using the RELU activation function and the output layer uses the softmax function. The loss is calculated using the sparse\_categorical\_crossentropy function. Dropout is used to prevent overfitting. We chose the Adam optimizer because it gave us the best results after evaluating other optimizers. The model accuracy can be increased by further increasing the epochs but after a certain period, we may achieve a threshold, so the value should be determined accordingly.

The model accuracy can be increased by further increasing the epochs but after a certain period, we may achieve a threshold, so the value should be determined accordingly. The accuracy we achieved for the test set is 92.14 percent which is very decent. So we come to the conclusion that Neural Networks are very effective in machine learning models. Tensorflow is very useful in implementing Convolutional Neural Network (CNN) that helps in the classifying process.