HUMAN ACTIVITY RECOGNITION USING SMARTPHONES

Importing packages needed

In [1]:
```
import tensorflow as tf
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Flatten, Dense, Dropout,BatchNormalizati
from tensorflow.keras.layers import Conv2D,MaxPool2D
from tensorflow.keras.optimizers import Adam
```

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
```

Reading dataset and assigning names to columns

In [15]:
```
columns = ['user', 'activity', 'time', 'x', 'y', 'z']
data = pd.read_csv('C:/Users/jiten/Downloads/WISDM.txt', header=None, names
```

Data Preprocessing

In [16]:
```
data = data.dropna()
data.head()
```

Out[16]:

	user	activity	time	x	y	z
0	33	Jogging	49105962326000	-0.694638	12.680544	0.503953
1	33	Jogging	49106062271000	5.012288	11.264028	0.953424
2	33	Jogging	49106112167000	4.903325	10.882658	-0.081722
3	33	Jogging	49106222305000	-0.612916	18.496431	3.023717
4	33	Jogging	49106332290000	-1.184970	12.108489	7.205164

In [17]:
```
1 data.tail()
```

Out[17]:

	user	activity	time	x	y	z
1098199	19	Sitting	131623331483000	9.00	-1.57	1.69
1098200	19	Sitting	131623371431000	9.04	-1.46	1.73
1098201	19	Sitting	131623411592000	9.08	-1.38	1.69
1098202	19	Sitting	131623491487000	9.00	-1.46	1.73
1098203	19	Sitting	131623531465000	8.88	-1.33	1.61

In [18]:
```
1 data.shape
```

Out[18]:
```
(1098203, 6)
```

In [19]:
```
1 data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1098203 entries, 0 to 1098203
Data columns (total 6 columns):
 #   Column    Non-Null Count    Dtype
---  ------    --------------    -----
 0   user      1098203 non-null  int64
 1   activity  1098203 non-null  object
 2   time      1098203 non-null  int64
 3   x         1098203 non-null  float64
 4   y         1098203 non-null  float64
 5   z         1098203 non-null  float64
dtypes: float64(3), int64(2), object(1)
memory usage: 58.7+ MB
```

In [20]:
```
1 data.isnull().sum()
```

Out[20]:
```
user        0
activity    0
time        0
x           0
y           0
z           0
dtype: int64
```

In [21]:
```
1 data['activity'].value_counts()
```

Out[21]:
```
Walking       424397
Jogging       342176
Upstairs      122869
Downstairs    100427
Sitting        59939
Standing       48395
Name: activity, dtype: int64
```

Ploting data according to activity for further understanding

In [22]:
```
Fs = 20
```

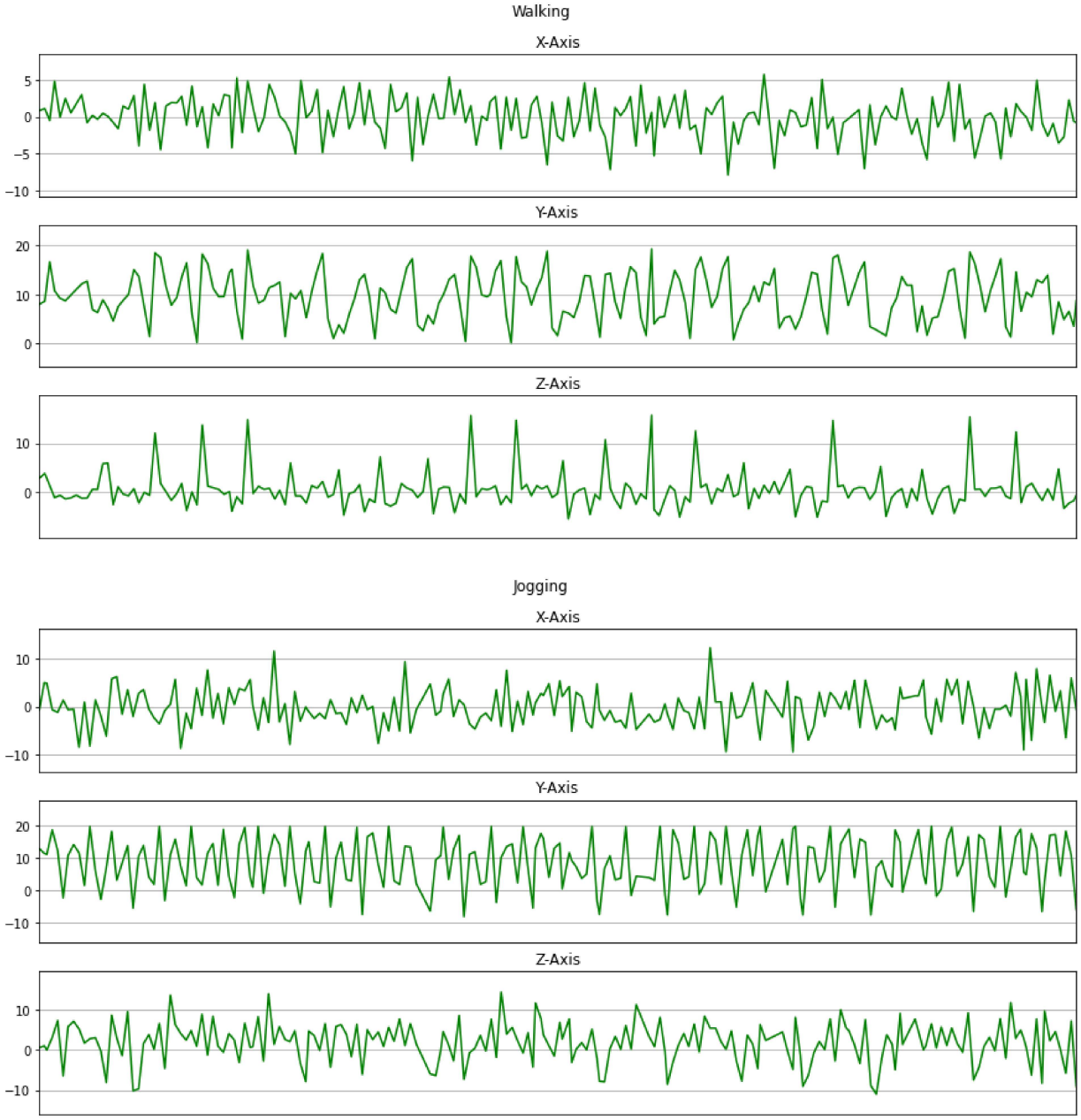
In [23]:
```
activities = data['activity'].value_counts().index
```

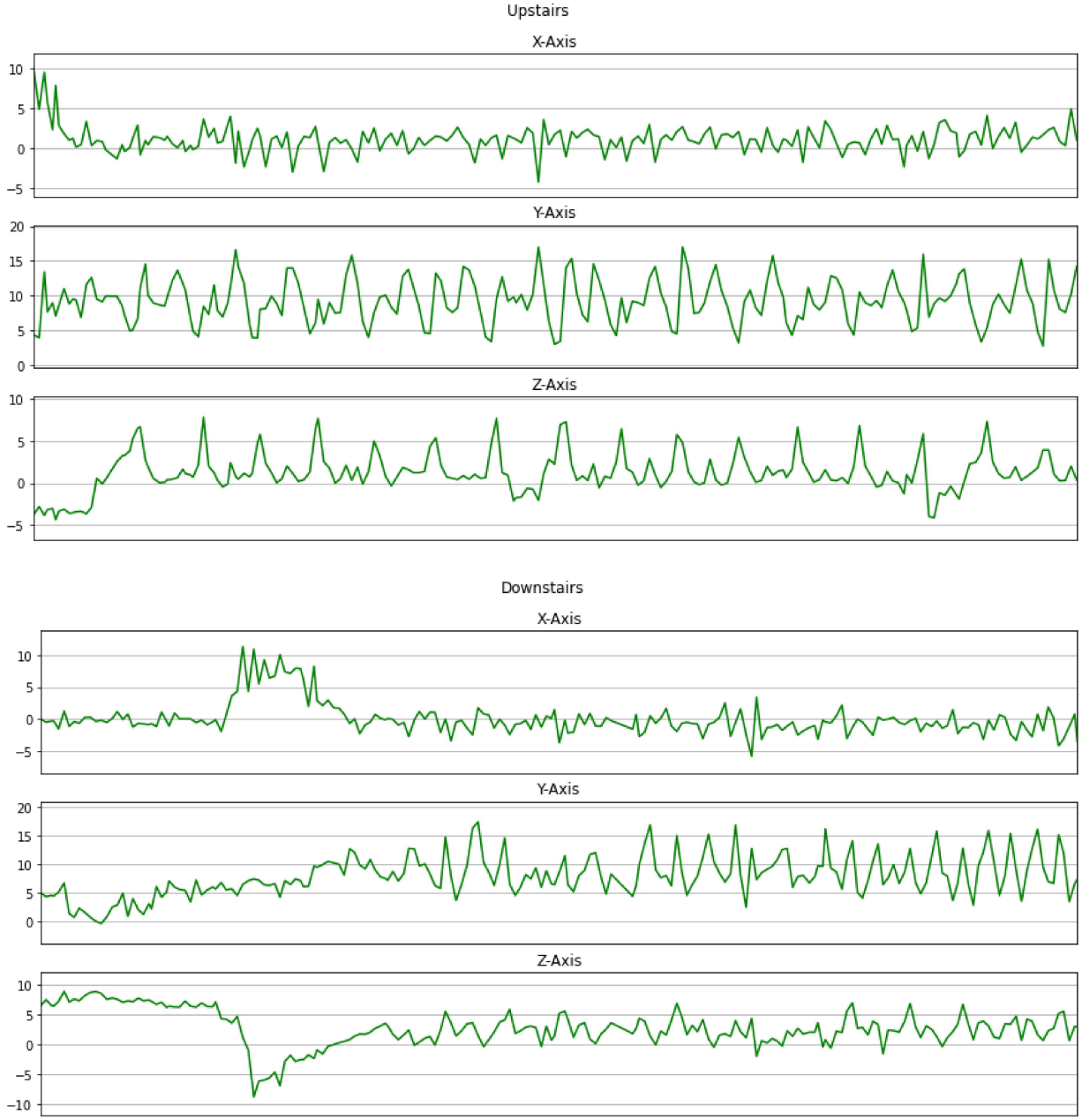
In [24]:
```
def plot_activity(activity,data):
  fig,(ax0,ax1,ax2) = plt.subplots(nrows=3, figsize=(15,7), sharex=True)
  plot_axis(ax0, data['time'],data['x'], 'X-Axis')
  plot_axis(ax1, data['time'],data['y'], 'Y-Axis')
  plot_axis(ax2, data['time'], data['z'], 'Z-Axis')
  plt.subplots_adjust(hspace=0.2)
  fig.suptitle(activity)
  plt.subplots_adjust(top=0.90)
  plt.show()
```

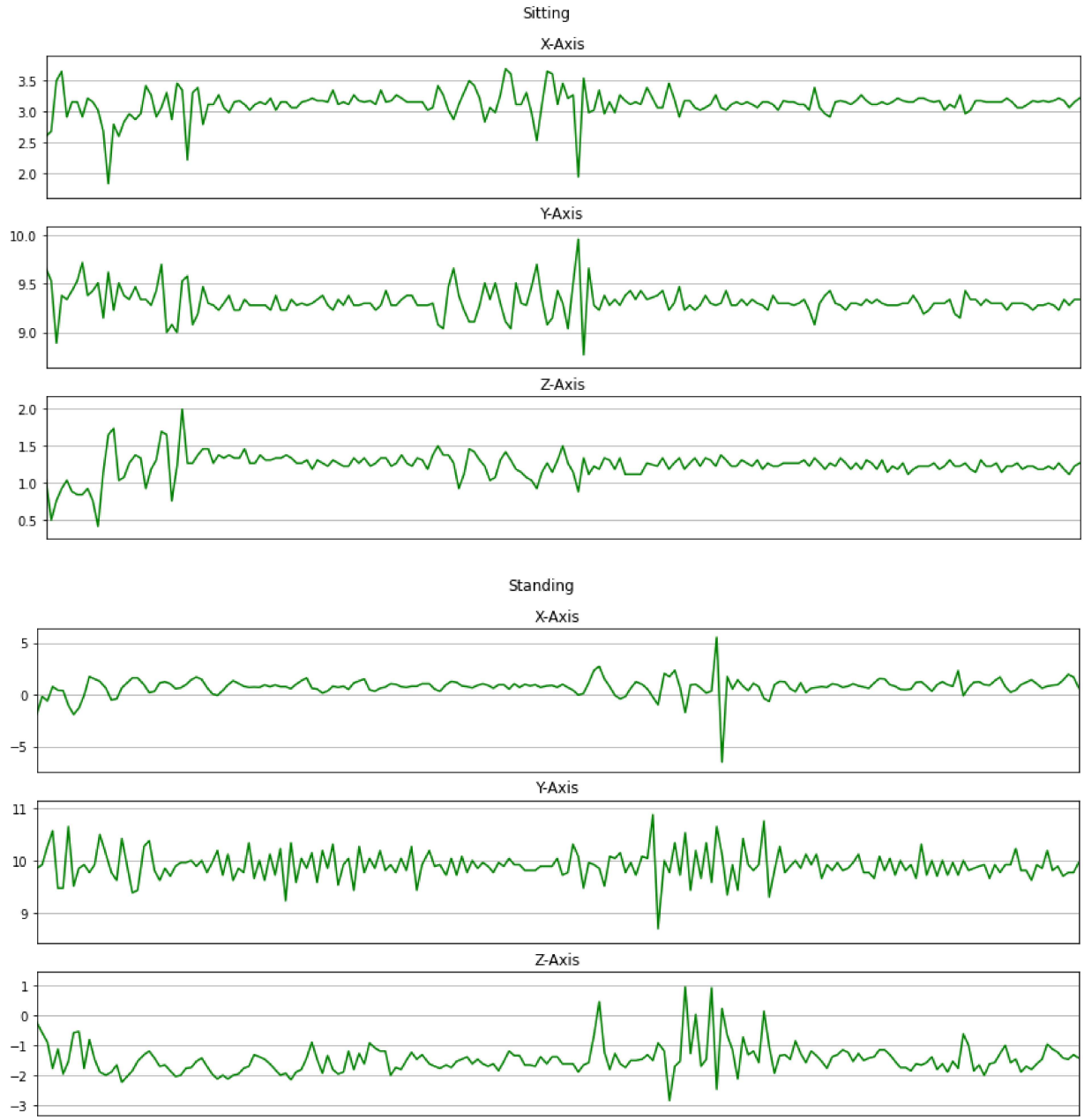
In [25]:

```
def plot_axis(ax,x,y,title):
  ax.plot(x, y, 'g')
  ax.set_title(title)
  ax.xaxis.set_visible(False)
  ax.set_ylim([min(y) - np.std(y), max(y) + np.std(y)])
  ax.set_xlim([min(x), max(x)])
  ax.grid(True)

for activity in activities:
  data_for_plot = data[(data['activity'] == activity)][:Fs*10]
  plot_activity(activity, data_for_plot)
```




Upstairs
X-Axis
Y-Axis
Z-Axis
Downstairs
X-Axis
Y-Axis
Z-Axis



Dropping unnecessary columns

In [26]:
```
df = data.drop(['user','time'], axis = 1).copy()
df.head()
```

Out[26]:

	activity	x	y	z
0	Jogging	-0.694638	12.680544	0.503953
1	Jogging	5.012288	11.264028	0.953424
2	Jogging	4.903325	10.882658	-0.081722
3	Jogging	-0.612916	18.496431	3.023717
4	Jogging	-1.184970	12.108489	7.205164

In [27]:
```
df['activity'].value_counts()
```

Out[27]:
```
Walking       424397
Jogging       342176
Upstairs      122869
Downstairs    100427
Sitting        59939
Standing       48395
Name: activity, dtype: int64
```

In [28]:
```
Walking = df[df['activity']=='Walking'].head(48395).copy()
Jogging = df[df['activity']=='Jogging'].head(48395).copy()
Upstairs = df[df['activity']=='Upstairs'].head(48395).copy()
Downstairs = df[df['activity']=='Downstairs'].head(48395).copy()
Sitting = df[df['activity']=='Sitting'].head(48395).copy()
Standing = df[df['activity']=='Standing'].head(48395).copy()
```

Creating a balanced dataset

In [29]:
```
balanced_data = pd.DataFrame()
balanced_data = balanced_data.append([Walking, Jogging, Upstairs, Downstairs
balanced_data.shape
```

Out[29]:
```
(290370, 4)
```

In [30]:
```
balanced_data['activity'].value_counts()
```

Out[30]:
```
Jogging       48395
Sitting       48395
Upstairs      48395
Walking       48395
Downstairs    48395
Standing      48395
Name: activity, dtype: int64
```

In [31]:
```
balanced_data.head()
```

Out[31]:

	activity	x	y	z
597	Walking	0.844462	8.008764	2.792171
598	Walking	1.116869	8.621680	3.786457
599	Walking	-0.503953	16.657684	1.307553
600	Walking	4.794363	10.760075	-1.184970
601	Walking	-0.040861	9.234595	-0.694638

Importing label encoder and encoding according to its activity

In [32]:
```
from sklearn.preprocessing import LabelEncoder
```

In [33]:
```
label = LabelEncoder()
balanced_data['label'] = label.fit_transform(balanced_data['activity'])
balanced_data.head()
```

Out[33]:

	activity	x	y	z	label
597	Walking	0.844462	8.008764	2.792171	5
598	Walking	1.116869	8.621680	3.786457	5
599	Walking	-0.503953	16.657684	1.307553	5
600	Walking	4.794363	10.760075	-1.184970	5
601	Walking	-0.040861	9.234595	-0.694638	5

In [34]:
```
label.classes_
```

Out[34]:
```
array(['Downstairs', 'Jogging', 'Sitting', 'Standing', 'Upstairs',
       'Walking'], dtype=object)
```

In [35]:
```
X = balanced_data[['x', 'y', 'z']]
y = balanced_data['label']
```

In [36]:
```
scaler  = StandardScaler()
X = scaler.fit_transform(X)

scaled_X = pd.DataFrame(data = X, columns = ['x','y','z'])
scaled_X['label'] = y.values
```

In [37]:
```
1 scaled_X
```

Out[37]:

	x	y	z	label
0	-0.034489	0.076967	0.266487	5
1	0.017285	0.187547	0.495750	5
2	-0.290769	1.637371	-0.075839	5
3	0.716230	0.573348	-0.650569	5
4	-0.202754	0.298127	-0.537507	5
...	...	...	...	...
290365	-1.143388	0.145748	-0.464958	3
290366	-1.169996	0.118686	-0.474181	3
290367	-1.061662	0.165594	-0.582554	3
290368	-1.046457	0.172811	-0.626365	3
290369	-1.133885	0.125903	-0.571025	3

290370 rows × 4 columns

Importing SciPy stats for stastical analysis of encoded data

In [38]:
```
1 import scipy.stats as stats
```

In [39]:
```
1 Fs = 20
2 frame_size = Fs*4
3 hop_size = Fs*2
```

In [40]:
```
def get_frames(df, frame_size, hop_size):
  N_FEATURES = 3

  frames = []
  labels  = []
  for i in range(0, len(df) - frame_size, hop_size):
      x = df['x'].values[i: i + frame_size]
      y = df['y'].values[i: i+ frame_size]
      z = df ['z'].values[i: i+frame_size]

      label = stats.mode(df['label'][i:i+frame_size])[0][0]
      frames.append([x,y,z])
      labels.append(label)

  frames = np.asarray(frames).reshape(-1, frame_size , N_FEATURES)
  label = np.asarray(labels)

  return frames,labels
```

In [ ]:
```
X, y = get_frames(scaled_X, frame_size, hop_size)
```

In [42]:
```
np.shape(X)
```

Out[42]: (7258, 80, 3)

In [43]:
```
np.shape(y)
```

Out[43]: (7258,)

Splitting data into test data and train data

In [44]:
```
x_train, x_test, y_train,y_test = train_test_split(X,y,test_size = 0.2, rand
```

In [45]:
```
x_train.shape , x_test.shape
```

Out[45]: ((5806, 80, 3), (1452, 80, 3))

In [46]:
```
x_train[0].shape, x_test[0].shape
```

Out[46]: ((80, 3), (80, 3))

In [47]:
```
x_train = x_train.reshape(5806,80,3,1)
x_test = x_test.reshape(1452,80,3,1)
```

In [48]:
```
x_train[0].shape, x_test[0].shape
```

Out[48]: ((80, 3, 1), (80, 3, 1))

In [49]:
```
x_train = np.asarray(x_train)
y_train = np.asarray(y_train)
x_test = np.asarray(x_test)
y_test = np.asarray(y_test)
```

Training the model

Setting model parameters

In [50]:
```
model = Sequential()
model.add(Conv2D(16,(2,2), activation = 'relu', input_shape = x_train[0].sha
model.add(Dropout(0.1))

model.add(Conv2D(32,(2,2), activation='relu'))
model.add(Dropout(0.2))

model.add(Flatten())

model.add(Dense(64, activation='relu'))
model.add(Dropout(0.5))

model.add(Dense(6, activation='softmax'))
```

Compilation and fitting model

In [51]:
```
model.compile(optimizer=Adam(learning_rate=0.001),loss= 'sparse_categorical_
history=model.fit(x_train,y_train, epochs = 10, validation_data=(x_test, y_t
```

```
Epoch 1/10
182/182 [==============================] - 2s 7ms/step - loss: 0.9000 - accurac
y: 0.6385 - val_loss: 0.5477 - val_accuracy: 0.7713
Epoch 2/10
182/182 [==============================] - 1s 7ms/step - loss: 0.5721 - accurac
y: 0.7601 - val_loss: 0.4640 - val_accuracy: 0.8113
Epoch 3/10
182/182 [==============================] - 1s 6ms/step - loss: 0.4966 - accurac
y: 0.7947 - val_loss: 0.4112 - val_accuracy: 0.8457
Epoch 4/10
182/182 [==============================] - 1s 6ms/step - loss: 0.4295 - accurac
y: 0.8250 - val_loss: 0.3707 - val_accuracy: 0.8574
Epoch 5/10
182/182 [==============================] - 1s 6ms/step - loss: 0.3730 - accurac
y: 0.8465 - val_loss: 0.3213 - val_accuracy: 0.8919
Epoch 6/10
182/182 [==============================] - 1s 6ms/step - loss: 0.3252 - accurac
y: 0.8688 - val_loss: 0.2895 - val_accuracy: 0.8994
Epoch 7/10
182/182 [==============================] - 1s 6ms/step - loss: 0.2955 - accurac
y: 0.8862 - val_loss: 0.2578 - val_accuracy: 0.9118
Epoch 8/10
182/182 [==============================] - 1s 6ms/step - loss: 0.2563 - accurac
y: 0.8986 - val_loss: 0.2455 - val_accuracy: 0.9174
Epoch 9/10
182/182 [==============================] - 1s 6ms/step - loss: 0.2344 - accurac
y: 0.9079 - val_loss: 0.2291 - val_accuracy: 0.9277
Epoch 10/10
182/182 [==============================] - 1s 6ms/step - loss: 0.2117 - accurac
y: 0.9232 - val_loss: 0.2091 - val_accuracy: 0.9311
```

Plotting curves for model's learning history analysis

In [52]:

```
def plot_learningCurve(history,epochs):

  epoch_range = range(1, epochs+1)
  plt.plot(epoch_range, history.history['accuracy'])
  plt.plot(epoch_range, history.history['val_accuracy'])
  plt.title('Model accuracy')
  plt.ylabel('Accuracy')
  plt.xlabel('Epoch')
  plt.legend(['Train','val'],loc='upper left')
  plt.show()

  plt.plot(epoch_range, history.history['loss'])
  plt.plot(epoch_range, history.history['val_loss'])
  plt.title('Model loss accuracy')
  plt.ylabel('Loss')
  plt.xlabel('Epoch')
  plt.legend(['Train','val'],loc='upper left')
  plt.show()

```

In [53]:
```
1 plot_learningCurve(history,10)
```