Human Activity Recognition using smart phones

April 20, 2022

1 Human Activity Recognition ML model

1.0.1 Importing libraries

[1]:
```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import matplotlib.cm as cm
import seaborn as sns

%matplotlib inline
```

[2]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.tree import DecisionTreeClassifier
```

[3]:
```
train_data = pd.read_csv('train.csv')
test_data = pd.read_csv('test.csv')

shape_x = train_data.shape
shape_y = test_data.shape
print("Training Data: ", shape_x)
print("Null values present in training data: ", train_data.isnull().values.any())

print("Testing Data: ", shape_y)
print("Null values present in testing data: ", test_data.isnull().values.any())
```

```
Training Data:  (7352, 563)
Null values present in training data:  False
Testing Data:  (2947, 563)
Null values present in testing data:  False
```

[4]:
```
train_data.head(10)
```

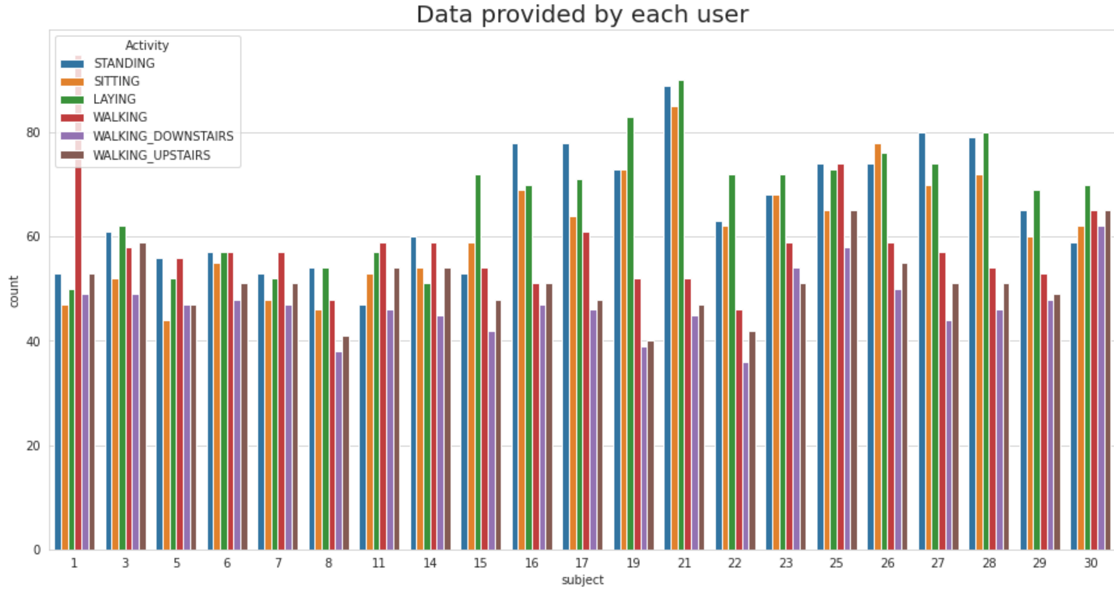
[4]:
```
   tBodyAcc-mean()-X  tBodyAcc-mean()-Y  tBodyAcc-mean()-Z  tBodyAcc-std()-X  \
0           0.288585          -0.020294          -0.132905         -0.995279
```

```
1          0.278419          -0.016411          -0.123520          -0.998245
2          0.279653          -0.019467          -0.113462          -0.995380
3          0.279174          -0.026201          -0.123283          -0.996091
4          0.276629          -0.016570          -0.115362          -0.998139
5          0.277199          -0.010098          -0.105137          -0.997335
6          0.279454          -0.019641          -0.110022          -0.996921
7          0.277432          -0.030488          -0.125360          -0.996559
8          0.277293          -0.021751          -0.120751          -0.997328
9          0.280586          -0.009960          -0.106065          -0.994803

   tBodyAcc-std()-Y  tBodyAcc-std()-Z  tBodyAcc-mad()-X  tBodyAcc-mad()-Y  \
0         -0.983111         -0.913526         -0.995112         -0.983185
1         -0.975300         -0.960322         -0.998807         -0.974914
2         -0.967187         -0.978944         -0.996520         -0.963668
3         -0.983403         -0.990675         -0.997099         -0.982750
4         -0.980817         -0.990482         -0.998321         -0.979672
5         -0.990487         -0.995420         -0.997627         -0.990218
6         -0.967186         -0.983118         -0.997003         -0.966097
7         -0.966728         -0.981585         -0.996485         -0.966313
8         -0.961245         -0.983672         -0.997596         -0.957236
9         -0.972758         -0.986244         -0.995405         -0.973663

   tBodyAcc-mad()-Z  tBodyAcc-max()-X  ...  fBodyBodyGyroJerkMag-kurtosis()  \
0         -0.923527         -0.934724  ...                        -0.710304
1         -0.957686         -0.943068  ...                        -0.861499
2         -0.977469         -0.938692  ...                        -0.760104
3         -0.989302         -0.938692  ...                        -0.482845
4         -0.990441         -0.942469  ...                        -0.699205
5         -0.995549         -0.942469  ...                        -0.844619
6         -0.983116         -0.940987  ...                        -0.564430
7         -0.982982         -0.940987  ...                        -0.421715
8         -0.984379         -0.940598  ...                        -0.572995
9         -0.985642         -0.940028  ...                         0.140452

   angle(tBodyAccMean,gravity)  angle(tBodyAccJerkMean),gravityMean)  \
0                    -0.112754                              0.030400
1                     0.053477                             -0.007435
2                    -0.118559                              0.177899
3                    -0.036788                             -0.012892
4                     0.123320                              0.122542
5                     0.082632                             -0.143439
6                    -0.212754                             -0.230622
7                    -0.020888                              0.593996
8                     0.012954                              0.080936
9                    -0.020590                             -0.127730

   angle(tBodyGyroMean,gravityMean)  angle(tBodyGyroJerkMean,gravityMean)  \
```

```
0                        -0.464761                      -0.018446
1                        -0.732626                       0.703511
2                         0.100699                       0.808529
3                         0.640011                      -0.485366
4                         0.693578                      -0.615971
5                         0.275041                      -0.368224
6                         0.014637                      -0.189512
7                        -0.561871                       0.467383
8                        -0.234313                       0.117797
9                        -0.482871                      -0.070670

   angle(X,gravityMean)  angle(Y,gravityMean)  angle(Z,gravityMean)  subject  \
0             -0.841247              0.179941             -0.058627        1
1             -0.844788              0.180289             -0.054317        1
2             -0.848933              0.180637             -0.049118        1
3             -0.848649              0.181935             -0.047663        1
4             -0.847865              0.185151             -0.043892        1
5             -0.849632              0.184823             -0.042126        1
6             -0.852150              0.182170             -0.043010        1
7             -0.851017              0.183779             -0.041976        1
8             -0.847971              0.188982             -0.037364        1
9             -0.848294              0.190310             -0.034417        1

   Activity
0  STANDING
1  STANDING
2  STANDING
3  STANDING
4  STANDING
5  STANDING
6  STANDING
7  STANDING
8  STANDING
9  STANDING

[10 rows x 563 columns]
```

[5]:

```
sns.set_style('whitegrid')
plt.rcParams['font.family'] = 'Dejavu Sans'

plt.figure(figsize=(16,8))
plt.title('Data provided by each user', fontsize=20)
sns.countplot(x='subject',hue='Activity', data = train_data)
plt.show()
```

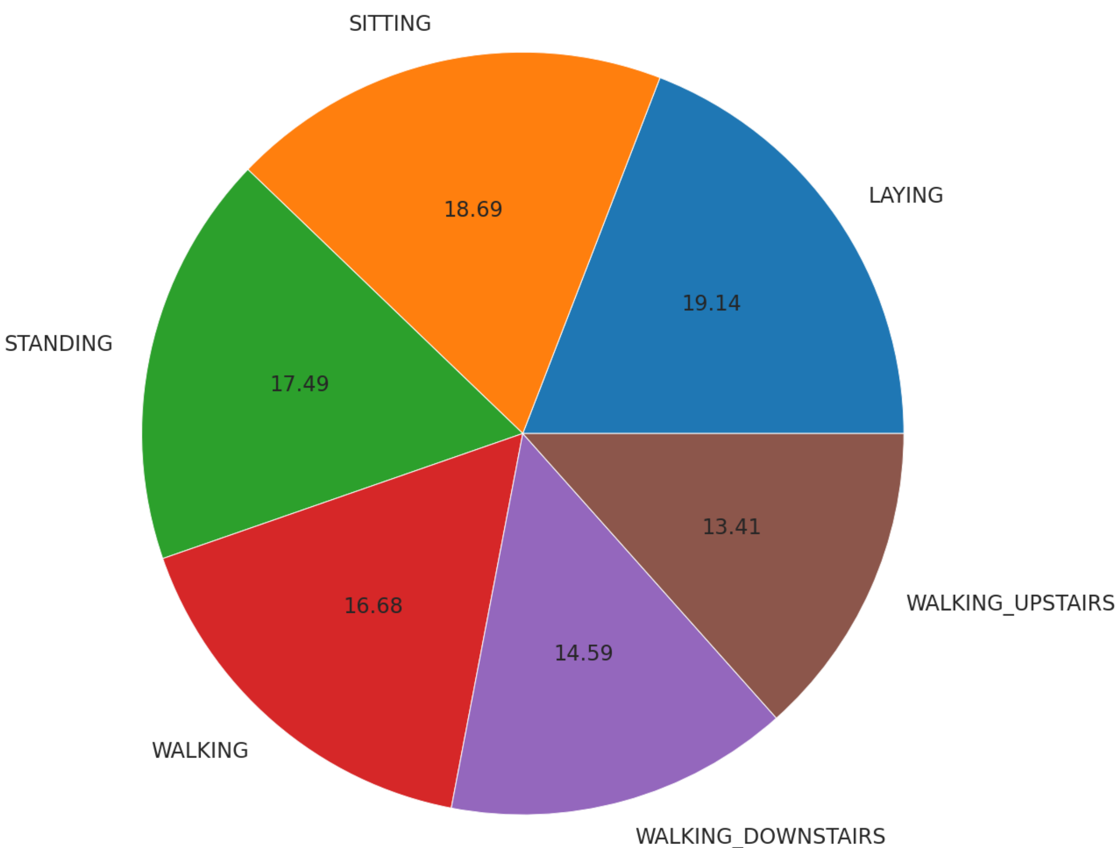


[6]:
```
# Get X and y for training data
y_train = train_data['Activity']
X_train = train_data.drop(columns = ['Activity', 'subject'])

# Get X and y for testing data
y_test = test_data['Activity']
X_test = test_data.drop(columns = ['Activity', 'subject'])
```

[7]:
```
# Count the number of records for each activity
count_of_each_activity = np.array(y_train.value_counts())

# Identify all the unqiue activities and in sorted order
activities = sorted(y_train.unique())

# Plot a pie chart for different activities
plt.rcParams.update({'figure.figsize': [20, 20], 'font.size': 24})
plt.pie(count_of_each_activity, labels = activities, autopct = '%0.2f')
```

[7]:
```
([<matplotlib.patches.Wedge at 0x19293742280>,
  <matplotlib.patches.Wedge at 0x19293742910>,
  <matplotlib.patches.Wedge at 0x19293742fa0>,
  <matplotlib.patches.Wedge at 0x19293751670>,
  <matplotlib.patches.Wedge at 0x19293751d00>,
  <matplotlib.patches.Wedge at 0x1929375f3d0>],
 [Text(0.9071064061014833, 0.6222201925441275, 'LAYING'),
  Text(-0.23874635466468208, 1.073778458591122, 'SITTING'),
  Text(-1.0745883152841482, 0.2350743555872831, 'STANDING'),
```

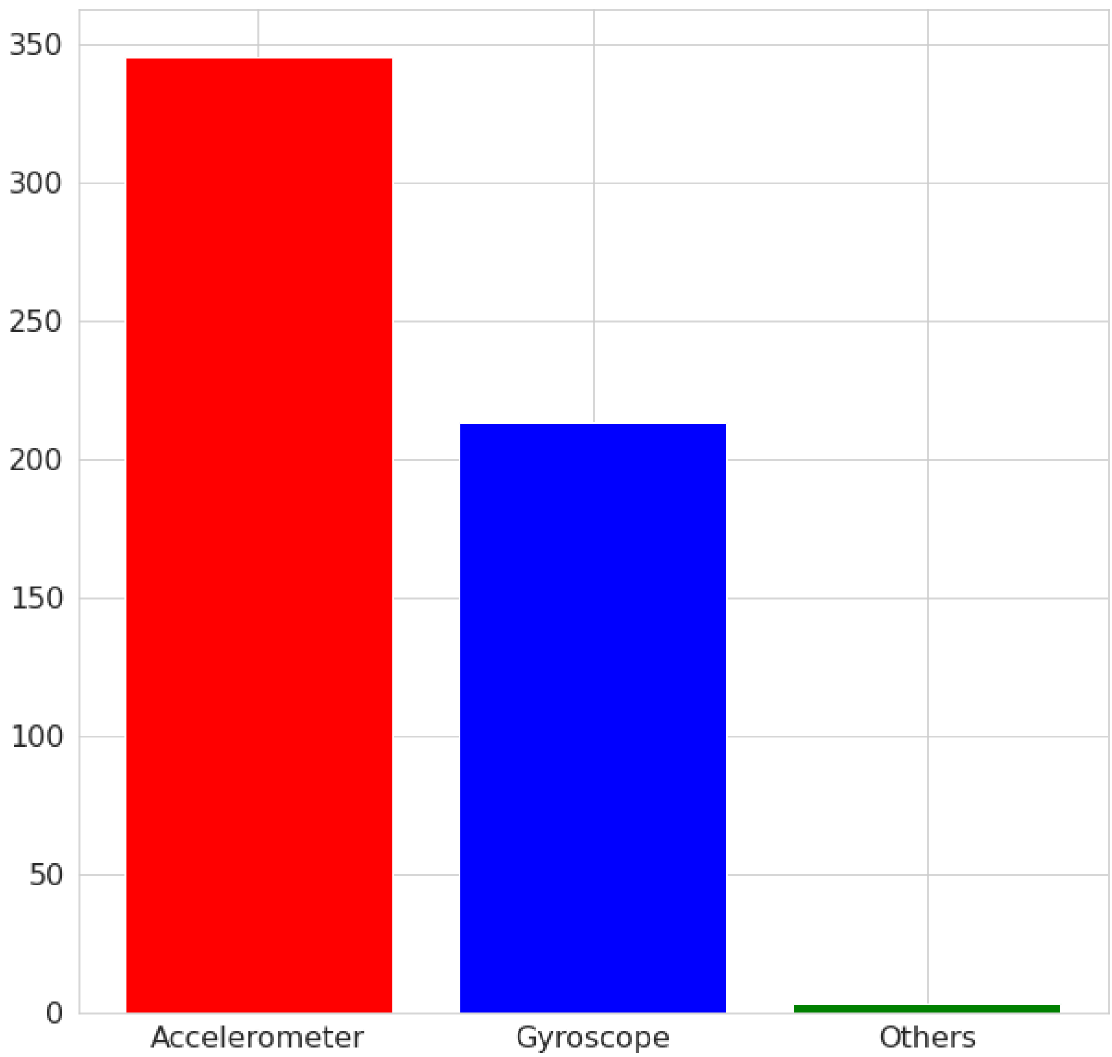
```
 Text(-0.7193129027755119, -0.832219290752544, 'WALKING'),
 Text(0.29301586483507763, -1.0602554894717366, 'WALKING_DOWNSTAIRS'),
 Text(1.0038008332903794, -0.4498709671511826, 'WALKING_UPSTAIRS')],
[Text(0.4947853124189908, 0.3393928322967968, '19.14'),
 Text(-0.13022528436255384, 0.5856973410497028, '18.69'),
 Text(-0.5861390810640807, 0.12822237577488166, '17.49'),
 Text(-0.3923524924230064, -0.453937794955933, '16.68'),
 Text(0.15982683536458778, -0.5783211760754926, '14.59'),
 Text(0.5475277272492978, -0.24538416390064502, '13.41')])
```



[8]:
```
# Count for each type
acc = 0
gyro = 0
others = 0
for column in X_train.columns:
    if 'Acc' in str(column):
        acc += 1
```

```python
    elif 'Gyro' in str(column):
        gyro += 1
    else:
        others += 1

# Show bar plot for the three types
plt.rcParams.update({'figure.figsize': [10, 10], 'font.size': 16})
plt.bar(['Accelerometer', 'Gyroscope', 'Others'], [acc, gyro, others], color =␣
 ↪('r', 'b', 'g'))
```

[8]: <BarContainer object of 3 artists>

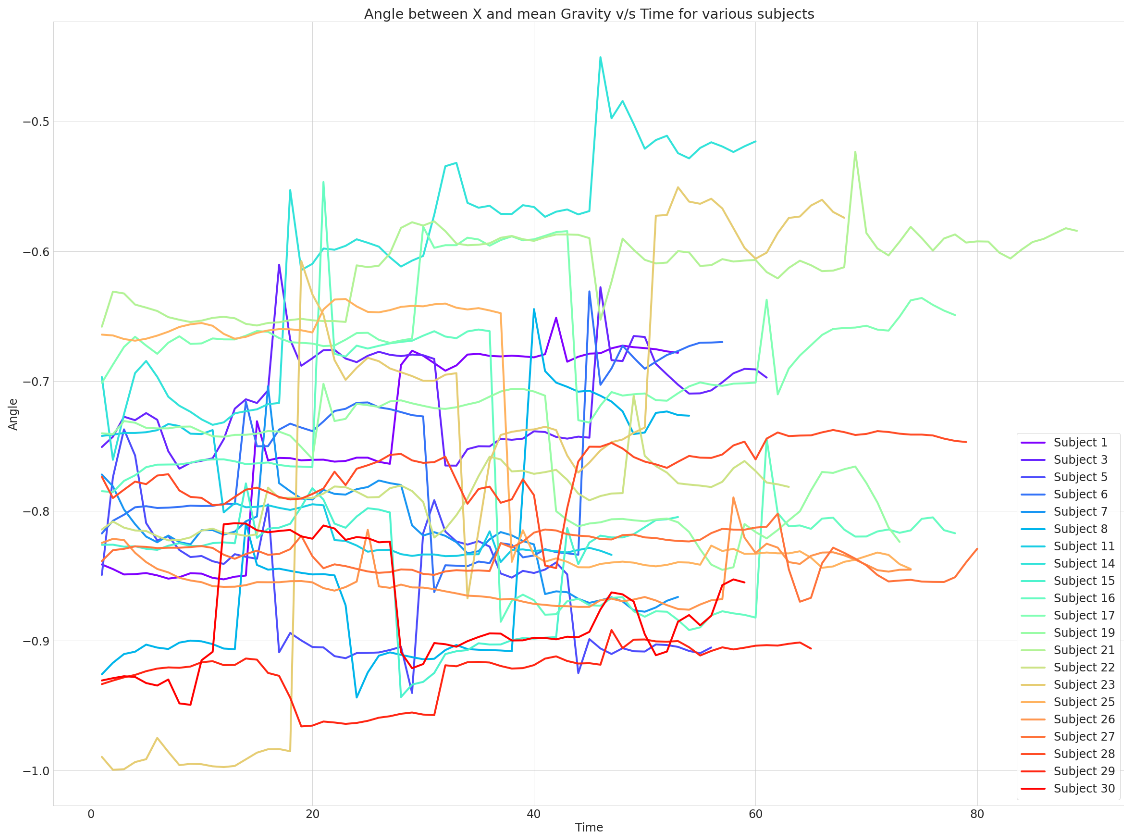


[9]:
```python
standing_activity = train_data[train_data['Activity'] == 'STANDING']
# Reset the index for this dataframe
```

```python
standing_activity = standing_activity.reset_index(drop=True)
```

[10]:
```python
# Set time series for each subject
time = 1
index = 0
time_series = np.zeros(standing_activity.shape[0])
for row_number in range(standing_activity.shape[0]):
    if (row_number == 0
        or standing_activity.iloc[row_number]['subject'] == standing_activity.
 ↪iloc[row_number - 1]['subject']):
        time_series[index] = time
        time += 1
    else:
        time_series[index] = 1
        time = 2
    index += 1

# Combine the time_series with the standing_activity dataframe
time_series_df = pd.DataFrame({ 'Time': time_series })
standing_activity_df = pd.concat([standing_activity, time_series_df], axis = 1)
```

[11]:
```python
colors = cm.rainbow(np.linspace(0, 1, len(standing_activity_df['subject'].
 ↪unique())))

# Create plot for each subject, which will all be displayed overlapping on one␣
 ↪plot
id = 0
for subject in standing_activity_df['subject'].unique():
    plt.rcParams.update({'figure.figsize': [40, 30], 'font.size': 24})
    plt.plot(standing_activity_df[standing_activity_df['subject'] ==␣
 ↪subject]['Time'],
             standing_activity_df[standing_activity_df['subject'] ==␣
 ↪subject]['angle(X,gravityMean)'],
             c = colors[id],
             label = 'Subject ' + str(subject),
             linewidth = 4)
    plt.xlabel('Time')
    plt.ylabel('Angle')
    plt.title('Angle between X and mean Gravity v/s Time for various subjects')
    plt.legend(prop = {'size': 24})
    id += 1
```



[12]:
```python
accuracy_scores = np.zeros(3)

# Logistic Regression
clf = LogisticRegression().fit(X_train, y_train)
prediction = clf.predict(X_test)
accuracy_scores[0] = accuracy_score(y_test, prediction)*100
print('Logistic Regression accuracy: {}%'.format(accuracy_scores[0]))
```

```
Logistic Regression accuracy: 95.89412962334578%
```

```
C:\Users\niket\anaconda3\lib\site-
packages\sklearn\linear_model\_logistic.py:763: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

[13]:
```
# K Nearest Neighbors
clf = KNeighborsClassifier().fit(X_train, y_train)
prediction = clf.predict(X_test)
accuracy_scores[1] = accuracy_score(y_test, prediction)*100
print('K Nearest Neighbors Classifier accuracy: {}%'.format(accuracy_scores[1]))
## Output:
# K Nearest Neighbors Classifier accuracy: 90.02375296912113%
```

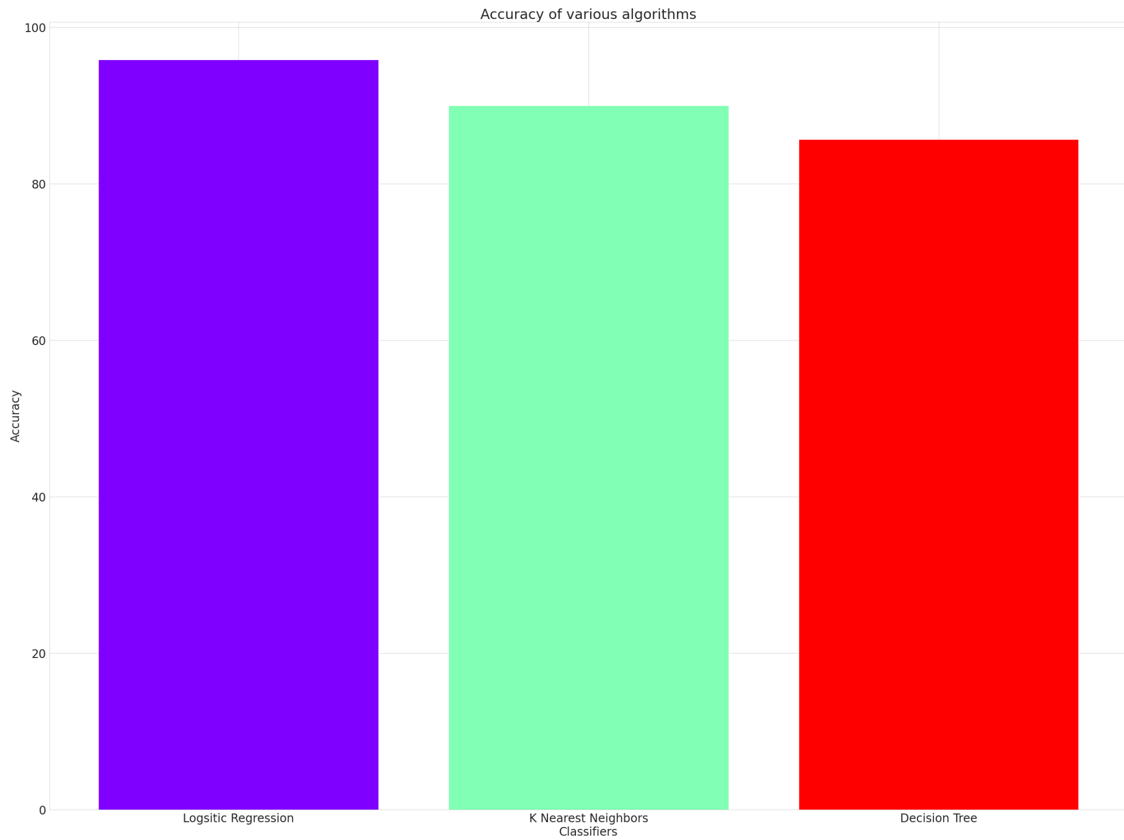
```
K Nearest Neighbors Classifier accuracy: 90.02375296912113%
```

[16]:
```
decisionTree = DecisionTreeClassifier(criterion="entropy", max_depth = None)
decisionTree # it shows the default parameters
decisionTree.fit(X_train,y_train)
predTree = decisionTree.predict(X_test)
accuracy_scores[2] =  accuracy_score(y_test, predTree)*100
print('Decision Tree Classifier accuracy: {}%'.format(accuracy_scores[2]))
```

```
Decision Tree Classifier accuracy: 85.71428571428571%
```

[18]:
```
colors = cm.rainbow(np.linspace(0, 1, 3))
labels = ['Logsitic Regression', 'K Nearest Neighbors', 'Decision Tree']
plt.bar(labels, accuracy_scores, color = colors)
plt.xlabel('Classifiers')
plt.ylabel('Accuracy')
plt.title('Accuracy of various algorithms')
```

[18]:
```
Text(0.5, 1.0, 'Accuracy of various algorithms')
```



Accuracy of various algorithms
Accuracy
0
20
40
60
80
100
Logsitic Regression
K Nearest Neighbors
Classifiers
Decision Tree

[ ]:

[ ]: