In [3]:
```
pip install termcolor
```

```
Collecting termcolor
  Downloading termcolor-1.1.0.tar.gz (3.9 kB)
Building wheels for collected packages: termcolor
  Building wheel for termcolor (setup.py): started
  Building wheel for termcolor (setup.py): finished with status 'done'
  Created wheel for termcolor: filename=termcolor-1.1.0-py3-none-any.whl size
=4835 sha256=274af8941db3dd27d91c75546257d4611ac11df0b6ba8b82b96467958a4f2192
  Stored in directory: c:\users\alokj\appdata\local\pip\cache\wheels\a0\16\9c
\5473df82468f958445479c59e784896fa24f4a5fc024b0f501
Successfully built termcolor
Installing collected packages: termcolor
Successfully installed termcolor-1.1.0
Note: you may need to restart the kernel to use updated packages.
```

In [50]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn import preprocessing
from termcolor import colored
from sklearn.metrics import classification_report
import matplotlib.pyplot as plt
```

In [ ]:
```
```

In [51]:
```
import os
import glob
```

In [52]:
```
glob.glob('./*.csv')
```

Out[52]:
```
['.\\browsing.csv',
 '.\\climbing.csv',
 '.\\running.csv',
 '.\\Travelling.csv',
 '.\\walking.csv']
```

In [53]:
```
output_label = {
 './Travelling.csv' : 'travel',
 './climbing.csv' : 'climb',
 './walking.csv' : 'walk',
 './running.csv' : 'run',
 './browsing.csv' : 'browse'
}
```

In [ ]:
```
```

In [54]:
```
dataset_train = {
    'time' : [],
    'gFx' : [],
    'gFy' : [],
    'gFz' : [],
    'TgF' : [],
    'class' : []
}

dataset_test = {
    'time' : [],
    'gFx' : [],
    'gFy' : [],
    'gFz' : [],
    'TgF' : [],
    'class' : []
}

for name in output_label.keys():
    df = pd.read_csv(name)

    flag = 0
    if name != './walking.csv' :
        for i in range(0,301, 10):
            flag+=1
            for key in dataset_train.keys():
                if key != 'class' :
                    if flag <= 25 :
                        dataset_train[key].append(df[df.time.between(i, i+10.0
)][key].mean())
                    else:
                        dataset_test[key].append(df[df.time.between(i, i+10.0
)][key].mean())
                else:
                    if flag <= 25 :
                        dataset_train[key].append(output_label[name])
                    else:
                        dataset_test[key].append(output_label[name])
    else:
        for i in range(0,70, 10):
            flag+=1
            for key in dataset_train.keys():
                if key != 'class' :
                    if flag <= 4 :
                        dataset_train[key].append(df[df.time.between(i, i+10.0
)][key].mean())
                    else:
                        dataset_test[key].append(df[df.time.between(i, i+10.0
)][key].mean())
                else:
                    if flag <= 4 :
                        dataset_train[key].append(output_label[name])
                    else:
                        dataset_test[key].append(output_label[name])
```

```
    print(name)
    print('='*50)
```

```
./Travelling.csv
==================================================
./climbing.csv
==================================================
./walking.csv
==================================================
./running.csv
==================================================
./browsing.csv
==================================================
```

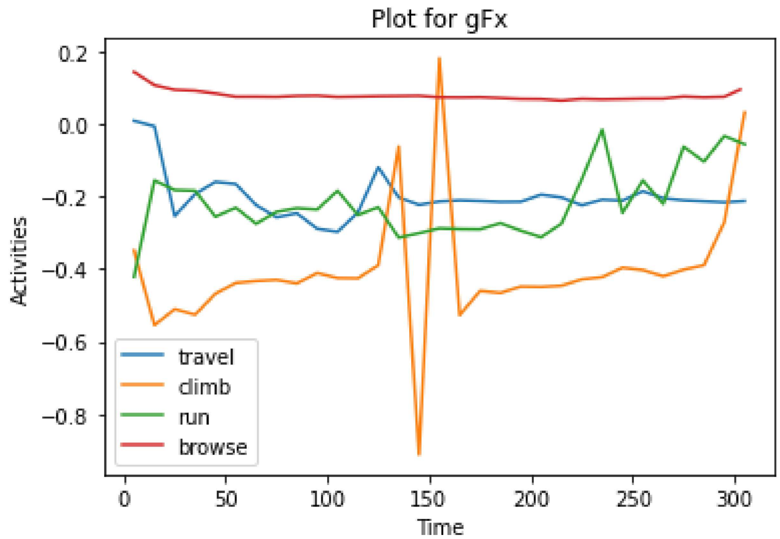
Visualization of Data

In [55]:
```
data_train = pd.DataFrame(dataset_train)
data_test = pd.DataFrame(dataset_test)

data = pd.concat([data_train, data_test])
```

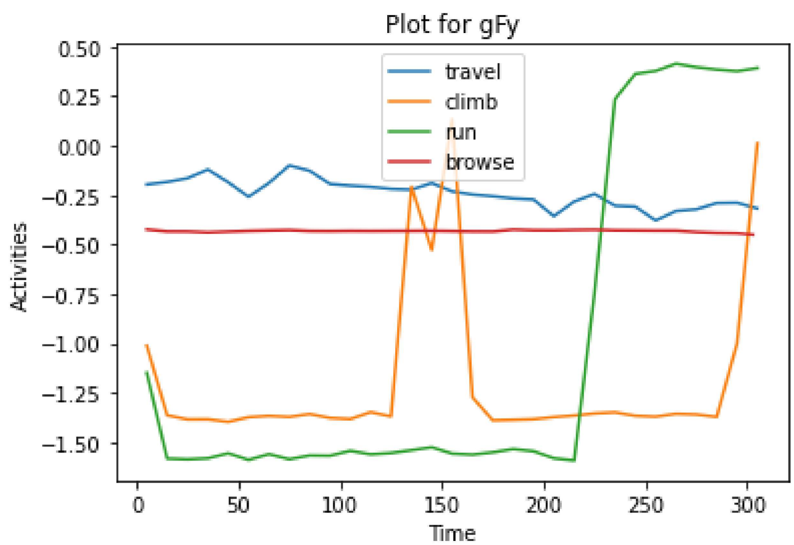
In [81]:
```
activities = [
    'travel',
    'climb',
     #'walk'
    'run',
    'browse'
    ]
```

In [83]:

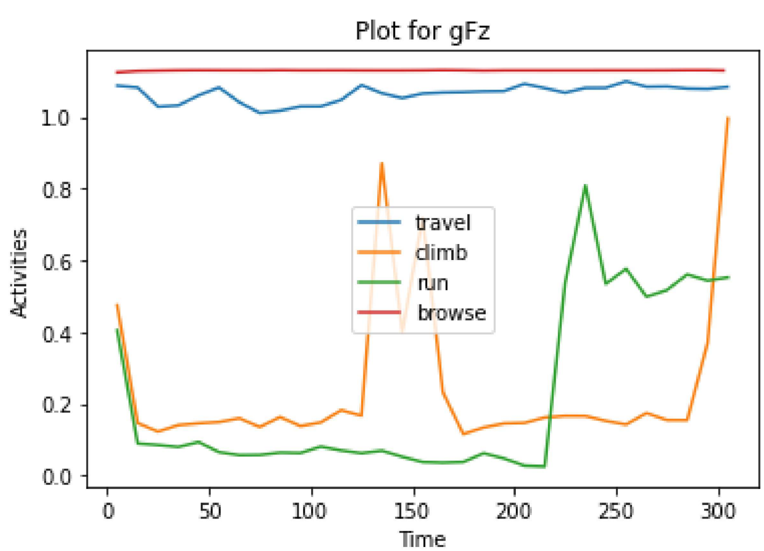
```
for feature in ['gFx','gFy', 'gFz','TgF' ]:
    for act in activities:
        plt.plot(data[data['class'] == act]["time"], data[data['class'] == act
][feature], label = act)
        plt.legend()

    plt.title("Plot for {}".format(feature))
    plt.xlabel('Time')
    plt.ylabel('Activities')
    plt.show()
    print(colored("="*50, 'green'))
```


Plot for gFx
0.2
0.0
−0.2
−0.4
−0.6
−0.8
Activities
0
50
100
150
200
250
300
Time
travel
climb
run
browse

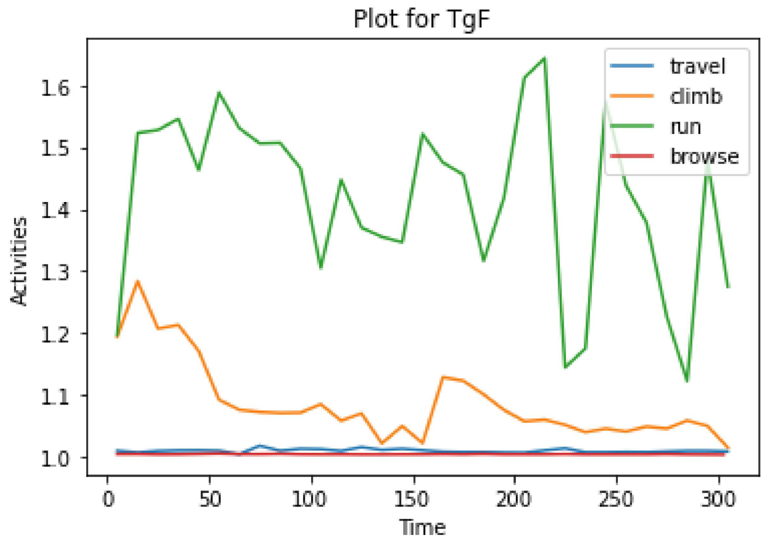
==


Plot for gFy
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
−1.25
−1.50
Activities
0
50
100
150
200
250
300
Time
travel
climb
run
browse

==


Plot for gFz
1.0
0.8
0.6
0.4
0.2
0.0
Activities
0
50
100
150
200
250
300
Time
travel
climb
run
browse

==

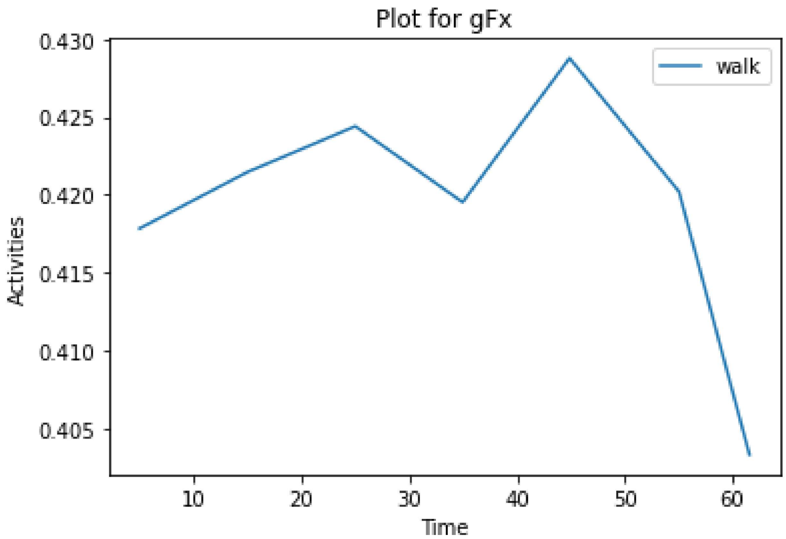


==

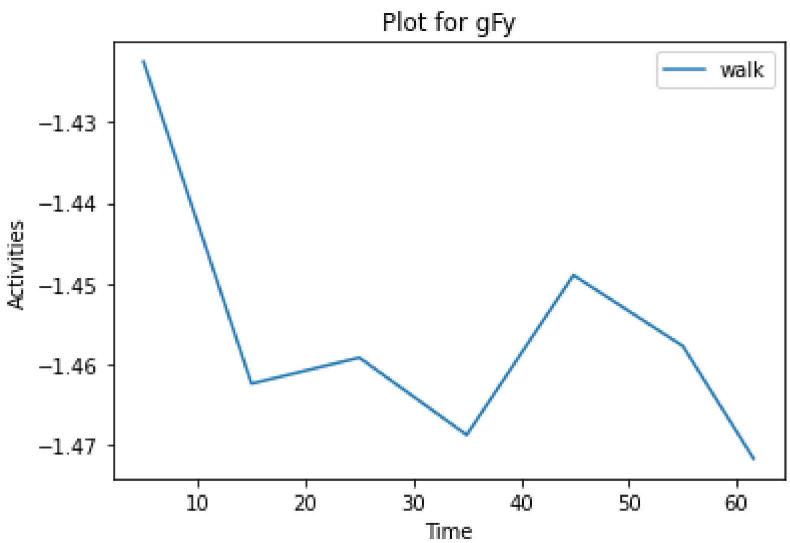
In [ ]:

In [84]:
```
activities = [
    #'travel',
    #'climb',
    'walk'
    #'run',
    #'browse'
    ]
```

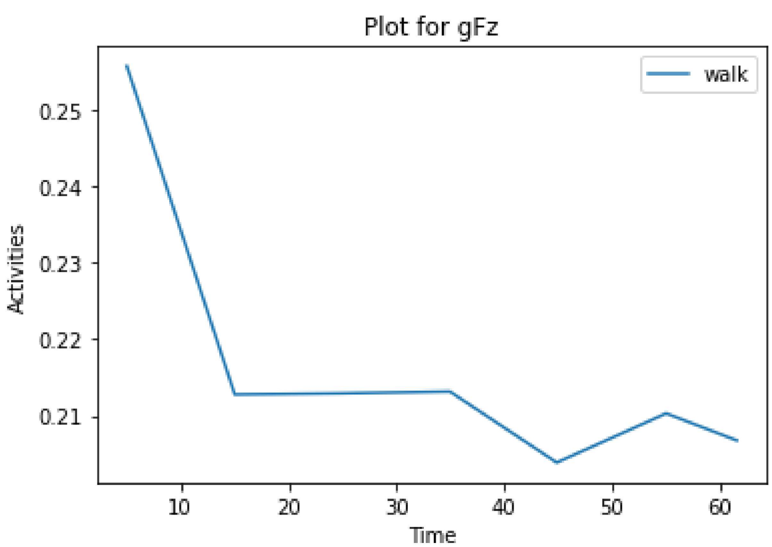
In [89]:
```
for feature in ['gFx','gFy', 'gFz','TgF' ]:

    for act in activities:
        plt.plot(data[data['class'] == act]["time"], data[data['class'] == act
][feature], label = act)
        plt.legend()

    plt.title("Plot for {}".format(feature))
    plt.xlabel('Time')
    plt.ylabel('Activities')
    plt.show()
    print(colored("="*50, 'green'))
```


Plot for gFx
walk
0.430
0.425
0.420
0.415
0.410
0.405
Activities
10
20
30
40
50
60
Time

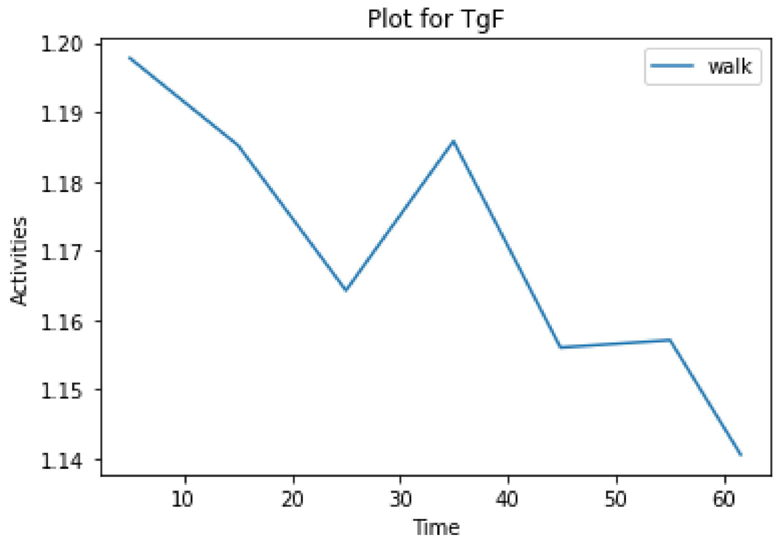
==


Plot for gFy
walk
−1.43
−1.44
−1.45
−1.46
−1.47
Activities
10
20
30
40
50
60
Time

==


Plot for gFz
walk
0.25
0.24
0.23
0.22
0.21
Activities
10
20
30
40
50
60
Time

==



==

In [ ]:

Feature Selection

features experimented with:

Mean

Standard Deviation

Skewness

specific transformation:

for travelling and runnig fourier transform is needed (to transform G-force) and the mean is sufficient for the remaining activities.

In [ ]:

Dataset Preparation for ML models

In [58]:
```
df_train = pd.DataFrame(dataset_train)[['gFx','gFy','gFz','TgF','class']]
```

In [59]:
```
df_test = pd.DataFrame(dataset_test)[['gFx','gFy','gFz','TgF','class']]
```

In [100]:
```
# scaler to normalize the input values

min_max_scaler = preprocessing.MinMaxScaler()
X_train = min_max_scaler.fit_transform(df_train[['gFx','gFy','gFz','TgF']])

# FFT-Transform:
from scipy import fftpack
X_fft = fftpack.fft(df_train[['gFx','gFy','gFz','TgF']])


#label encoder
label_encoder = preprocessing.LabelEncoder()
label_encoder = label_encoder.fit(df_train['class'].values)
y_train = label_encoder.transform(df_train['class'].values)


## get the test set

X_test = min_max_scaler.transform(df_test[['gFx','gFy','gFz','TgF']])
y_test = label_encoder.transform(df_test['class'].values)
```

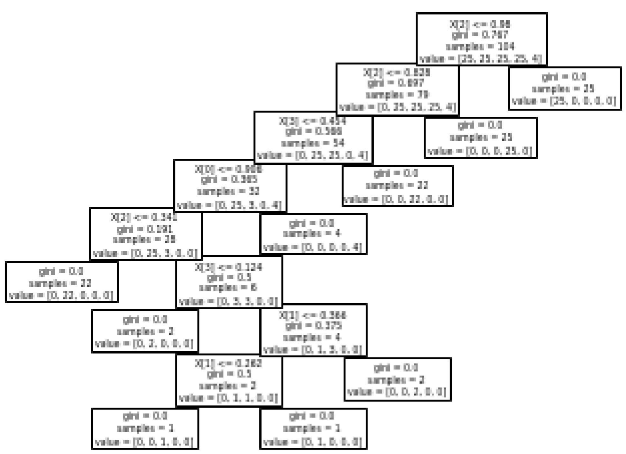
Decision Tree

In [101]:
```
from sklearn import tree
```

In [102]:
```
clf = tree.DecisionTreeClassifier()
clf = clf.fit(X_train, y_train)
```

In [103]:
```
tree.plot_tree(clf)
```

Out[103]:
```
[Text(251.10000000000002, 205.35999999999999, 'X[2] <= 0.98\ngini = 0.767\nsa
mples = 104\nvalue = [25, 25, 25, 25, 4]'),
 Text(209.25, 181.2, 'X[2] <= 0.828\ngini = 0.697\nsamples = 79\nvalue = [0,
25, 25, 25, 4]'),
 Text(167.4, 157.04, 'X[3] <= 0.454\ngini = 0.566\nsamples = 54\nvalue = [0,
25, 25, 0, 4]'),
 Text(125.55000000000001, 132.88, 'X[0] <= 0.906\ngini = 0.365\nsamples = 32
\nvalue = [0, 25, 3, 0, 4]'),
 Text(83.7, 108.72, 'X[2] <= 0.341\ngini = 0.191\nsamples = 28\nvalue = [0, 2
5, 3, 0, 0]'),
 Text(41.85, 84.56, 'gini = 0.0\nsamples = 22\nvalue = [0, 22, 0, 0, 0]'),
 Text(125.55000000000001, 84.56, 'X[3] <= 0.124\ngini = 0.5\nsamples = 6\nval
ue = [0, 3, 3, 0, 0]'),
 Text(83.7, 60.400000000000006, 'gini = 0.0\nsamples = 2\nvalue = [0, 2, 0,
0, 0]'),
 Text(167.4, 60.400000000000006, 'X[1] <= 0.366\ngini = 0.375\nsamples = 4\nv
alue = [0, 1, 3, 0, 0]'),
 Text(125.55000000000001, 36.24000000000001, 'X[1] <= 0.262\ngini = 0.5\nsamp
les = 2\nvalue = [0, 1, 1, 0, 0]'),
 Text(83.7, 12.079999999999984, 'gini = 0.0\nsamples = 1\nvalue = [0, 0, 1,
0, 0]'),
 Text(167.4, 12.079999999999984, 'gini = 0.0\nsamples = 1\nvalue = [0, 1, 0,
0, 0]'),
 Text(209.25, 36.24000000000001, 'gini = 0.0\nsamples = 2\nvalue = [0, 0, 2,
0, 0]'),
 Text(167.4, 108.72, 'gini = 0.0\nsamples = 4\nvalue = [0, 0, 0, 0, 4]'),
 Text(209.25, 132.88, 'gini = 0.0\nsamples = 22\nvalue = [0, 0, 22, 0, 0]'),
 Text(251.10000000000002, 157.04, 'gini = 0.0\nsamples = 25\nvalue = [0, 0,
0, 25, 0]'),
 Text(292.95, 181.2, 'gini = 0.0\nsamples = 25\nvalue = [25, 0, 0, 0, 0]')]
```



In [104]:
```
dt_predicted = clf.predict(X_test)
dt_predicted
```

Out[104]:
```
array([3, 3, 3, 3, 3, 3, 1, 1, 1, 1, 1, 3, 4, 4, 4, 2, 2, 2, 2, 2, 2, 0,
       0, 0, 0, 0, 0])
```

In [105]:
```
y_test
```
Out[105]:
```
array([3, 3, 3, 3, 3, 3, 1, 1, 1, 1, 1, 1, 4, 4, 4, 2, 2, 2, 2, 2, 2, 0,
       0, 0, 0, 0, 0])
```

SVM Classifier

In [66]:
```
from sklearn import svm
```
In [67]:
```
clf_svm = svm.SVC()
```
In [68]:
```
clf_svm.fit(X_train, y_train)
```
Out[68]:
```
SVC()
```
In [69]:
```
svm_predicted = clf_svm.predict(X_test)
```

Logistic Regression

In [70]:
```
from sklearn.linear_model import LogisticRegression
```
In [71]:
```
clf = LogisticRegression(random_state=0)
clf.fit(X_train, y_train)
```
Out[71]:
```
LogisticRegression(random_state=0)
```
In [72]:
```
lr_predicted = clf.predict(X_test)
```

KNN

In [90]:
```
from sklearn.neighbors import KNeighborsClassifier
```
In [91]:
```
neigh = KNeighborsClassifier(n_neighbors=5)
```
In [92]:
```
neigh.fit(X_train, y_train)
```
Out[92]:
```
KNeighborsClassifier()
```
In [93]:
```
knn_predicted = neigh.predict(X_test)
```

Performance Analysis

In [94]:
```
matrix = pd.DataFrame({
    "Decision_Tree" : label_encoder.inverse_transform(dt_predicted),
    "SVM" : label_encoder.inverse_transform(svm_predicted),
    "Logistic_Regression" : label_encoder.inverse_transform(lr_predicted),
    "KNN" : label_encoder.inverse_transform(knn_predicted),
    "y_test" : label_encoder.inverse_transform(y_test)
})
```

In [95]:
```
matrix.head()
```

Out[95]:

	Decision_Tree	SVM	Logistic_Regression	KNN	y_test
0	travel	travel	travel	travel	travel
1	travel	travel	travel	travel	travel
2	travel	travel	travel	travel	travel
3	travel	travel	travel	travel	travel
4	travel	travel	travel	travel	travel

As we can see below: "Decision Tree" and "SVM" performs better than that of KNN and Logistic Regression for the give classification problem.

In [96]:
```
matrix
```

Out[96]:

	Decision_Tree	SVM	Logistic_Regression	KNN	y_test
0	travel	travel	travel	travel	travel
1	travel	travel	travel	travel	travel
2	travel	travel	travel	travel	travel
3	travel	travel	travel	travel	travel
4	travel	travel	travel	travel	travel
5	travel	travel	travel	travel	travel
6	climb	climb	climb	climb	climb
7	climb	climb	climb	climb	climb
8	climb	climb	climb	climb	climb
9	climb	climb	climb	climb	climb
10	climb	climb	climb	climb	climb
11	travel	travel	travel	travel	climb
12	walk	walk	run	walk	walk
13	walk	walk	run	walk	walk
14	walk	walk	run	walk	walk
15	run	run	run	run	run
16	run	run	run	run	run
17	run	run	travel	run	run
18	run	climb	travel	climb	run
19	run	run	run	run	run
20	run	run	travel	run	run
21	browse	browse	browse	browse	browse
22	browse	browse	browse	browse	browse
23	browse	browse	browse	browse	browse
24	browse	browse	browse	browse	browse
25	browse	browse	browse	browse	browse
26	browse	browse	browse	browse	browse

In [97]:
```
for model in ["Decision_Tree","SVM","Logistic_Regression","KNN"] :
    print(colored("For Model : {} , Classification Report is : ".format(model
),'magenta'))
    print(classification_report(matrix["y_test"].values, matrix[model].values
))
    print('='*50)
```

```
For Model : Decision_Tree , Classification Report is :
              precision    recall  f1-score   support

      browse       1.00      1.00      1.00         6
       climb       1.00      0.83      0.91         6
         run       1.00      1.00      1.00         6
      travel       0.86      1.00      0.92         6
        walk       1.00      1.00      1.00         3

    accuracy                           0.96        27
   macro avg       0.97      0.97      0.97        27
weighted avg       0.97      0.96      0.96        27

==================================================
For Model : SVM , Classification Report is :
              precision    recall  f1-score   support

      browse       1.00      1.00      1.00         6
       climb       0.83      0.83      0.83         6
         run       1.00      0.83      0.91         6
      travel       0.86      1.00      0.92         6
        walk       1.00      1.00      1.00         3

    accuracy                           0.93        27
   macro avg       0.94      0.93      0.93        27
weighted avg       0.93      0.93      0.93        27

==================================================
For Model : Logistic_Regression , Classification Report is :
              precision    recall  f1-score   support

      browse       1.00      1.00      1.00         6
       climb       1.00      0.83      0.91         6
         run       0.50      0.50      0.50         6
      travel       0.60      1.00      0.75         6
        walk       0.00      0.00      0.00         3

    accuracy                           0.74        27
   macro avg       0.62      0.67      0.63        27
weighted avg       0.69      0.74      0.70        27

==================================================
For Model : KNN , Classification Report is :
              precision    recall  f1-score   support

      browse       1.00      1.00      1.00         6
       climb       0.83      0.83      0.83         6
         run       1.00      0.83      0.91         6
      travel       0.86      1.00      0.92         6
        walk       1.00      1.00      1.00         3

    accuracy                           0.93        27
   macro avg       0.94      0.93      0.93        27
weighted avg       0.93      0.93      0.93        27

==================================================
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\_classification.p
y:1221: UndefinedMetricWarning: Precision and F-score are ill-defined and bei
ng set to 0.0 in labels with no predicted samples. Use `zero_division` parame
ter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

Analysis of Algorithms

mean is best suited feature among [mean, std, skewness] as per the classifiction report which includes precision,recall and f1_measure. """ """

In [ ]: