PROJECT: Classifying Cow’s activities

AIM : Classify Cow’s activities into 9 categories based on Data collected from IMU SENSORS

Data

IMU Data (Accelerometer, Gyroscope, Magnetometer)

What is IMU?

Inertial measurement unit, used to describe a collection of measurement tools, when installed in some device, catches movement with the help of accelerometer, gyroscope and magnetometer, in 3d space.

Variable names:-

- acc_x,acc_y,acc_z: accelerometer output for all 3 dimensions movement.
- gyr_x,gyr_y,gyr_z: gyroscope outputs, it measures rotation, rotation rate (angular velocity).
- mag_x,mag_y,mag_z: magnetometer outputs, catches magnetic field around the device.
- All three (Acc, Gyr, Mag) gives output in different SI Units i.e The scale for all three are different, so Data must be normalized

Classes and their Encoded values:-

- eating = 1
- drinking = 2
- walking = 3
- standing =4
- lying = 5
- ruminating standing = 6
- ruminating lying = 7
- grooming = 8
- idle/other = 9

Notebook Contents :

1. Dataset Information
2. Exploratory Data Analysis (EDA)
3. Feature Engineering
4. Modeling
5. Conclusion

1. Dataset Information

In [1]:
```
#importing the common libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
#importing the dataset
drinking = pd.read_csv(r'D:\dsap class\project\COW DATASET\Classify cow positions
eating = pd.read_csv(r'D:\dsap class\project\COW DATASET\Classify cow positions u
walking = pd.read_csv(r'D:\dsap class\project\COW DATASET\Classify cow positions
grooming = pd.read_csv(r'D:\dsap class\project\COW DATASET\Classify cow positions
idle = pd.read_csv(r'D:\dsap class\project\COW DATASET\Classify cow positions usi
lying = pd.read_csv(r'D:\dsap class\project\COW DATASET\Classify cow positions us
ruminating_lying = pd.read_csv(r'D:\dsap class\project\COW DATASET\Classify cow p
ruminating_standing = pd.read_csv(r'D:\dsap class\project\COW DATASET\Classify co
standing = pd.read_csv(r'D:\dsap class\project\COW DATASET\Classify cow positions
```

In [3]:
```
# concatenating all the csv files
df = pd.concat([drinking, eating, walking, grooming, idle, lying, ruminating_lyir
```

In [4]:
```
#viewing the concatenated dataset
df
```

Out[4]:

	time	acc_x	acc_y	acc_z	gyr_x	gyr_y	gyr_z	mag_x	ma
0	1628079761	-0.187012	1.071289	0.321289	7.934570	-40.527344	17.028809	-526.5	14
1	1628079761	-0.137207	1.099121	0.294922	0.305176	-44.677734	15.930176	-528.0	14
2	1628079761	0.028320	1.053711	0.215820	-9.216309	-42.541504	10.681152	-510.0	14
3	1628079761	0.151856	0.960938	0.206543	-15.502930	-31.433105	4.943848	-529.5	14
4	1628079761	0.171387	0.883301	0.247070	-0.061035	-27.832031	-2.685547	-526.5	14
...	...	...	...	...	...	...	...	...	
2539801	1628397674	0.296875	0.908691	0.293457	0.000000	-1.953125	3.540039	-643.5	8
2539802	1628397674	0.298828	0.915527	0.294434	0.610352	-2.624512	2.563477	-637.5	9
2539803	1628397674	0.301270	0.911133	0.295410	1.037598	-2.746582	3.112793	-622.5	8
2539804	1628397674	0.301758	0.920410	0.284668	2.014160	-2.868652	3.662109	-621.0	9
2539805	1628397674	0.301270	0.911133	0.289062	0.915527	-2.319336	2.868652	-645.0	9

12263524 rows × 11 columns

In [5]:
```
#to check the number of rows n columns
df.shape
```

Out[5]:
```
(12263524, 11)
```

In [6]:
```
#checking for null values
df.isnull().sum()
```

Out[6]:
```
time     0
acc_x    0
acc_y    0
acc_z    0
gyr_x    0
gyr_y    0
gyr_z    0
mag_x    0
mag_y    0
mag_z    0
label    0
dtype: int64
```

2. Exploratory Data Analysis

In [7]:
```
#checking how many rows and columns are present
df.shape
```

Out[7]:
```
(12263524, 11)
```

In [8]:
```
#getting to know the column names
df.columns
```

Out[8]:
```
Index(['time', 'acc_x', 'acc_y', 'acc_z', 'gyr_x', 'gyr_y', 'gyr_z', 'mag_x',
       'mag_y', 'mag_z', 'label'],
      dtype='object')
```

In [9]:
```python
#creating a function to create a table that has feature_name, dtype, missing valu
def insights_table(df):
    summary = pd.DataFrame(df.dtypes,columns=['dtypes'])
    summary = summary.reset_index()
    summary['Feature_name'] = summary['index']
    summary = summary[['Feature_name','dtypes']]
    summary['Missing_values'] = df.isnull().sum().values
    summary['No. Uniques_values'] = df.nunique().values
    return summary
insights_table(df)
```

Out[9]:

	Feature_name	dtypes	Missing_values	No. Uniques_values
0	time	int64	0	106341
1	acc_x	float64	0	6843
2	acc_y	float64	0	9373
3	acc_z	float64	0	7552
4	gyr_x	float64	0	9525
5	gyr_y	float64	0	11236
6	gyr_z	float64	0	6473
7	mag_x	float64	0	1280
8	mag_y	float64	0	1920
9	mag_z	float64	0	1404
10	label	int64	0	9

Observation:

1. Missing Data : we don't have any missing data.
2. There is no object type data, all are either int or float.

In [10]:
```python
df.describe()
```

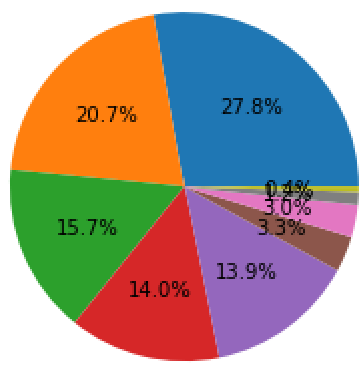
Out[10]:

	time	acc_x	acc_y	acc_z	gyr_x	gyr_y
count	1.226352e+07	1.226352e+07	1.226352e+07	1.226352e+07	1.226352e+07	1.226352e+07
mean	1.628243e+09	-2.807402e-02	6.211683e-01	1.081455e-01	8.722215e-01	-1.837340e+00
std	1.205662e+05	2.622167e-01	7.084800e-01	1.888613e-01	1.282481e+01	2.014151e+01
min	1.628067e+09	-1.599756e+01	-1.314160e+01	-1.599121e+01	-1.999756e+03	-1.998779e+03
25%	1.628106e+09	-2.182617e-01	8.281250e-01	3.173830e-02	-2.014160e+00	-5.676270e+00
50%	1.628312e+09	-2.490230e-02	9.370118e-01	1.230469e-01	8.544922e-01	-1.892090e+00
75%	1.628335e+09	1.616211e-01	9.736329e-01	2.006836e-01	3.723145e+00	1.892090e+00
max	1.628421e+09	1.051514e+01	1.182617e+01	1.599854e+01	1.999756e+03	1.999939e+03

In [11]:
```
df['label'].value_counts()
```

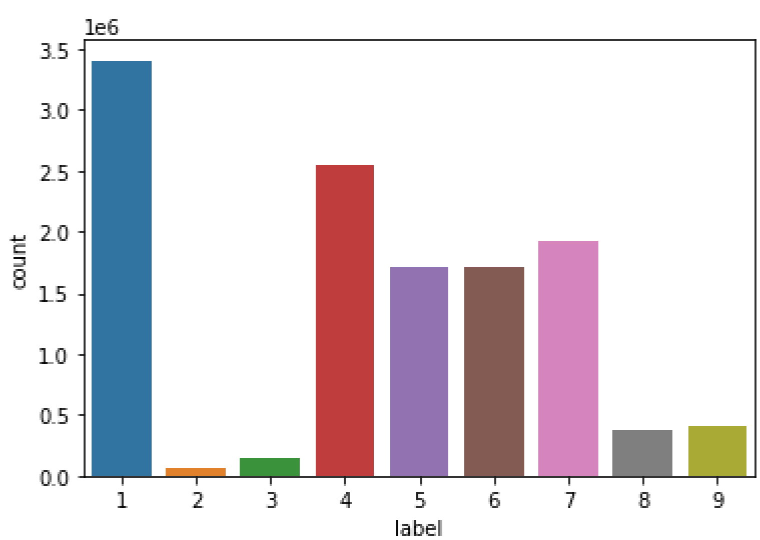
Out[11]:
```
1    3405702
4    2539806
7    1928968
5    1711687
6    1703683
9     405263
8     368607
3     145369
2      54439
Name: label, dtype: int64
```

In [12]:
```
#distribution of df
plt.pie(df['label'].value_counts(), autopct = '%1.1f%%')
plt.show()
```



In [13]:
```
#understanding our target variable
sns.countplot(df['label'])
```

Out[13]: <AxesSubplot:xlabel='label', ylabel='count'>



In [14]:
```
#checking the percentage of each class of the target variable present in the data
(df['label'].value_counts()/len(df['label']))*100
```

Out[14]:
```
1    27.770990
4    20.710246
7    15.729312
5    13.957546
6    13.892279
9     3.304621
8     3.005718
3     1.185377
2     0.443910
Name: label, dtype: float64
```

Observation:

The target variables are imbalanced!

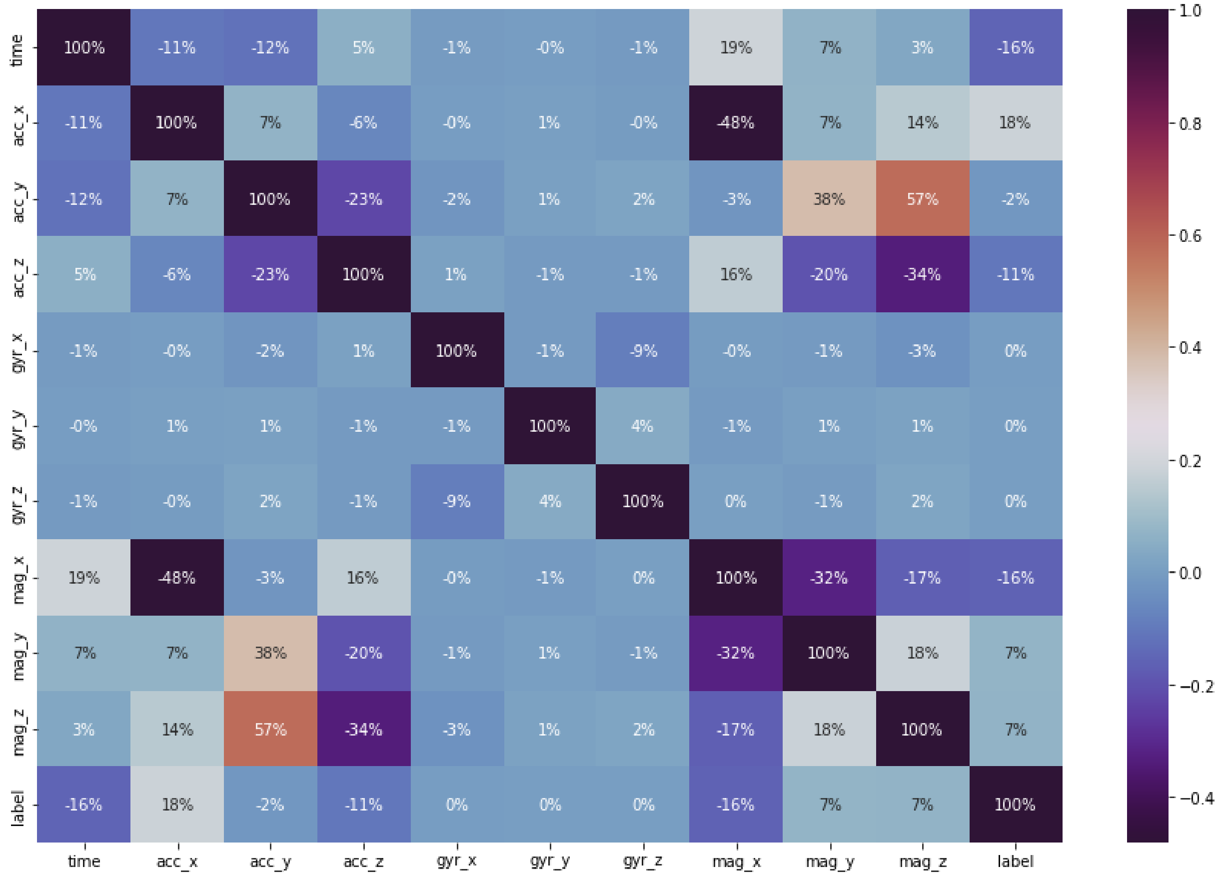
Correlation

In [15]:
```
df.corr()
```

Out[15]:

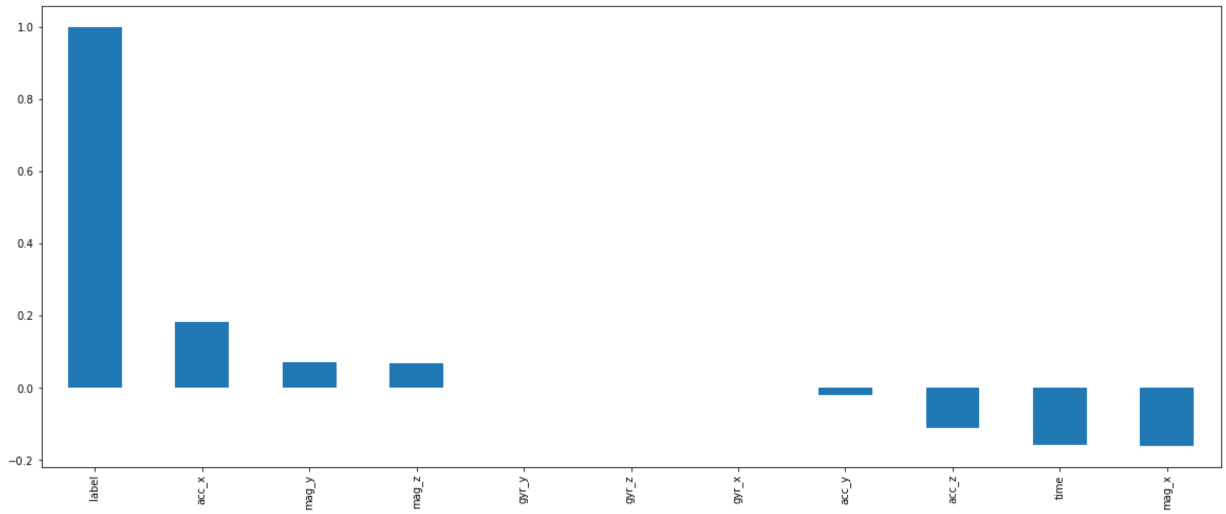
	time	acc_x	acc_y	acc_z	gyr_x	gyr_y	gyr_z	mag_x	m
time	1.000000	-0.108821	-0.118527	0.054428	-0.005030	-0.002011	-0.008394	0.187664	0.06
acc_x	-0.108821	1.000000	0.068235	-0.064783	-0.001430	0.006372	-0.004203	-0.481286	0.06
acc_y	-0.118527	0.068235	1.000000	-0.227910	-0.023733	0.006674	0.020762	-0.025147	0.38
acc_z	0.054428	-0.064783	-0.227910	1.000000	0.012389	-0.009027	-0.010025	0.157934	-0.19
gyr_x	-0.005030	-0.001430	-0.023733	0.012389	1.000000	-0.009946	-0.088246	-0.004642	-0.00
gyr_y	-0.002011	0.006372	0.006674	-0.009027	-0.009946	1.000000	0.041503	-0.008726	0.00
gyr_z	-0.008394	-0.004203	0.020762	-0.010025	-0.088246	0.041503	1.000000	0.004679	-0.00
mag_x	0.187664	-0.481286	-0.025147	0.157934	-0.004642	-0.008726	0.004679	1.000000	-0.32
mag_y	0.066354	0.068210	0.382588	-0.198680	-0.009834	0.005924	-0.006413	-0.323132	1.00
mag_z	0.032587	0.144633	0.574042	-0.337945	-0.033924	0.013075	0.022479	-0.168128	0.17
label	-0.156390	0.181582	-0.018375	-0.109248	0.000211	0.002118	0.001470	-0.160687	0.07

In [16]:
```
#checking the correlation between all the features
plt.figure(figsize=(15,10))
cor = df.corr()
sns.heatmap(cor,annot = True, cmap="twilight_shifted", fmt = '.0%' )
plt.show()
```

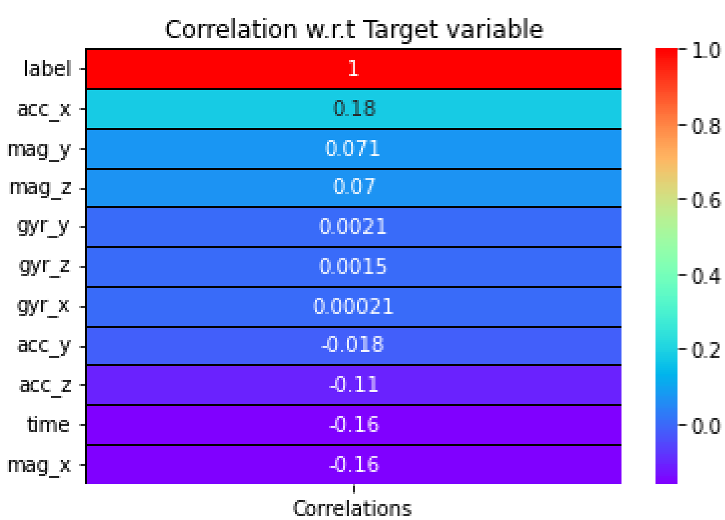


In [17]:
```
plt.figure(figsize=(20,8))
df.corr()['label'].sort_values(ascending = False).plot(kind='bar')
```

Out[17]: <AxesSubplot:>



In [18]:
```
corr = df.corrwith(df['label']).sort_values(ascending = False).to_frame()
corr.columns = ['Correlations']
sns.heatmap(corr,annot = True,cmap = 'rainbow',linewidths = 0.6,linecolor = 'blac
plt.title('Correlation w.r.t Target variable');
```



Seperating the dependent and independent variables

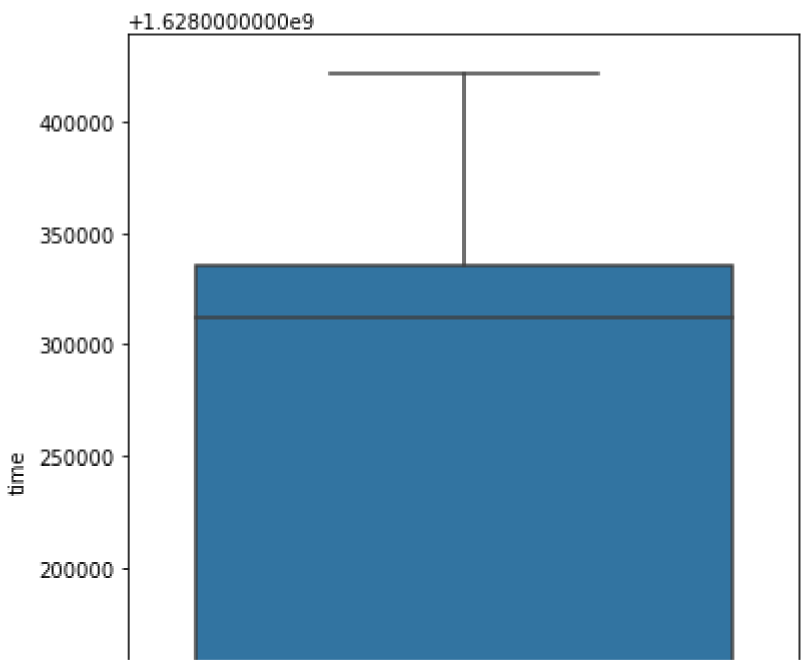
In [19]:
```
#seperating the x and y variables
x = df.drop('label', axis = 1) #independent features
#x = df.iloc[:,:-1]

y = df['label'] #dependent features
#y = df.iloc[:,-1]
```

In [20]:
```
#defining a variable named column_name n giving it all the column names expect la
column_name = ['time','acc_x', 'acc_y', 'acc_z', 'gyr_x', 'gyr_y', 'gyr_z', 'mag_
```

Checking for outliers

In [21]:
```
# Using a for loop inside a function to get the box plots(seaborn) of all the col
def identify_outliers(give_df_name, give_column_name):
    for i in column_name:
        fig = plt.figure(figsize=(6,8))
        sns.boxplot(data = x, y = i)
plt.show()
```

In [22]:
```
identify_outliers(x, column_name)
```



3. Feature Engineering

Replacing the outliers with meadian value

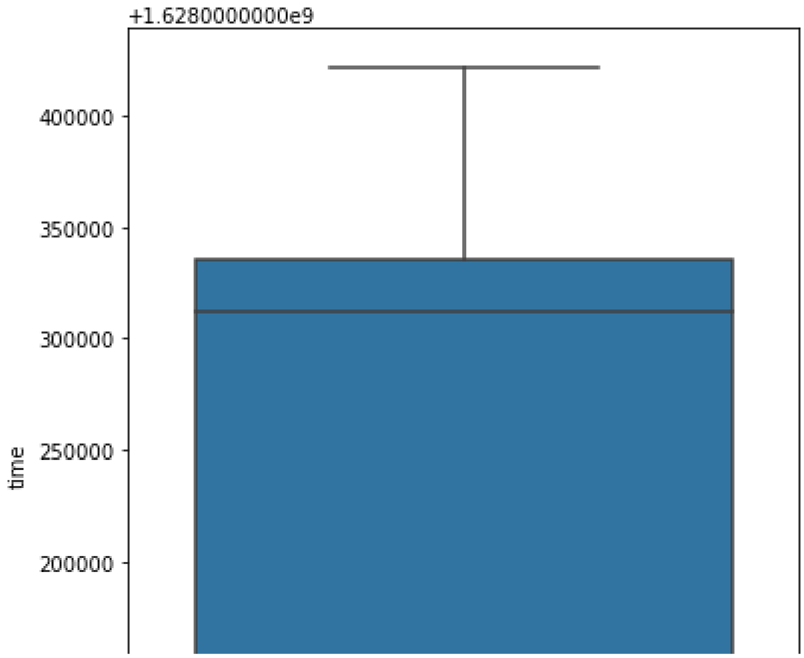
In [23]:
```
# Using a for loop inside a function to replace the outliers with median value
def replace_outlier(x, column_name):
    for i in column_name:
        print('column name : ',i)
        Q1 = np.percentile(x[i], 25)
        Q2 = np.percentile(x[i], 50)
        Q3 = np.percentile(x[i], 75)
        IQR = Q3 - Q1
        print('Q1 =',Q1,'Q2 = ',Q2,'Q3 = ',Q3)

        upper_val = Q3 + (1.5 * IQR)
        print('upper', upper_val)
        lower_val = Q1 - (1.5 * IQR)
        print('lower', lower_val)

        x.loc[x[i] > upper_val, i] = np.median(x[i])
        x.loc[x[i] < lower_val, i] = np.median(x[i])

        fig = plt.figure(figsize = (6,8))
        sns.boxplot(data = x,y = i)
        plt.xticks(rotation = 'horizontal')
        plt.show()
```

In [24]:
```
replace_outlier(x, column_name)
```

```
column name :  time
Q1 = 1628105948.0 Q2 =  1628312235.0 Q3 =  1628335043.0
upper 1628678685.5
lower 1627762305.5
```

looking for outliers after imputing with median

In [25]:
```
identify_outliers(x, column_name)
```



Observation

Outliers are now imputed with the median value

Normalization

All three (Acc, Gyr, Mag) gives output in different SI Units i.e The scale for all three are different, so Data must be normalized

In [26]:
```
from sklearn.preprocessing import MinMaxScaler
scaling = MinMaxScaler()
scaling.fit_transform(x)
```

Out[26]:
```
array([[0.03725611, 0.3953713 , 0.79278516, ..., 0.32814238, 0.83820565,
        0.6369583 ],
       [0.03725611, 0.42815819, 0.84060391, ..., 0.32703003, 0.83366935,
        0.62714636],
       [0.03725611, 0.53712634, 0.76258386, ..., 0.3403782 , 0.83215726,
        0.62142273],
       ...,
       [0.93311879, 0.71681137, 0.51761761, ..., 0.25695217, 0.65272177,
        0.47751431],
       [0.93311879, 0.71713276, 0.53355714, ..., 0.25806452, 0.66078629,
        0.46197874],
       [0.93311879, 0.71681137, 0.51761761, ..., 0.24026696, 0.6577621 ,
        0.4627964 ]])
```

In [27]:
```
x_normalized = pd.DataFrame(scaling.fit_transform(x))
x_normalized.head(3)
```

Out[27]:

	0	1	2	3	4	5	6	7	8	9
0	0.037256	0.395371	0.792785	0.803907	0.810160	0.5	0.5	0.328142	0.838206	0.636958
1	0.037256	0.428158	0.840604	0.764834	0.475936	0.5	0.5	0.327030	0.833669	0.627146
2	0.037256	0.537126	0.762584	0.647612	0.058824	0.5	0.5	0.340378	0.832157	0.621423

In [28]:
```
x_normalized = pd.DataFrame(scaling.fit_transform(x),columns = x.columns)
x_normalized.head(3)
```

Out[28]:

	time	acc_x	acc_y	acc_z	gyr_x	gyr_y	gyr_z	mag_x	mag_y	mag_z
0	0.037256	0.395371	0.792785	0.803907	0.810160	0.5	0.5	0.328142	0.838206	0.636958
1	0.037256	0.428158	0.840604	0.764834	0.475936	0.5	0.5	0.327030	0.833669	0.627146
2	0.037256	0.537126	0.762584	0.647612	0.058824	0.5	0.5	0.340378	0.832157	0.621423

Feature Selection

Selecting KBest Features using chi2

In [29]:
```
#select k best
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
```

In [30]:
```
#ranking the features
select_k_best_rank_features = SelectKBest(score_func = chi2, k = 5)
k_best_features = select_k_best_rank_features.fit(x_normalized,y)

df_k_scores = pd.DataFrame(k_best_features.scores_, columns = ['score'])
dfcolumns = pd.DataFrame(x_normalized.columns)

k_best_feature_rank = pd.concat([dfcolumns, df_k_scores], axis = 1)

k_best_feature_rank.columns = ('features', 'k_score')
print(k_best_feature_rank.nlargest(6, 'k_score'))
```

```
  features        k_score
0     time  551696.294963
1    acc_x  150058.553659
7    mag_x  106664.110641
8    mag_y   67694.199464
3    acc_z   43636.740650
2    acc_y   36914.462173
```

Observation:

- From chi2 we see that the top 6 features are time, acc_x, mag_x, mag_y, acc_z, acc_y

Creating a new dataframe with x_normalized and y values/

In [32]:
```
new_df = x_normalized
new_df['label'] = y.values
new_df
```

Out[32]:

	time	acc_x	acc_y	acc_z	gyr_x	gyr_y	gyr_z	mag_x	mag_
0	0.037256	0.395371	0.792785	0.803907	0.810160	0.500000	0.500000	0.328142	0.83820
1	0.037256	0.428158	0.840604	0.764834	0.475936	0.500000	0.500000	0.327030	0.83366
2	0.037256	0.537126	0.762584	0.647612	0.058824	0.500000	0.500000	0.340378	0.83215
3	0.037256	0.618451	0.603188	0.633864	0.500000	0.500000	0.837037	0.325918	0.83518
4	0.037256	0.631308	0.469799	0.693922	0.459893	0.500000	0.374074	0.328142	0.83266
...	...	...	...	...	...	...	...	...	.
12263519	0.933119	0.713918	0.513423	0.762663	0.462567	0.497976	0.751852	0.241379	0.65121
12263520	0.933119	0.715204	0.525168	0.764110	0.489305	0.475709	0.692593	0.245829	0.65877
12263521	0.933119	0.716811	0.517618	0.765557	0.508021	0.471660	0.725926	0.256952	0.65272
12263522	0.933119	0.717133	0.533557	0.749638	0.550802	0.467611	0.759259	0.258065	0.66078
12263523	0.933119	0.716811	0.517618	0.756150	0.502674	0.485830	0.711111	0.240267	0.65776

12263524 rows × 11 columns

4. Modeling

As the Dataset is quite huge,

i. lets take sample data from population data

ii. build a differnt model on each sample

iii. check which model gives good results

Sample 1 - df1 - Logistic Regression

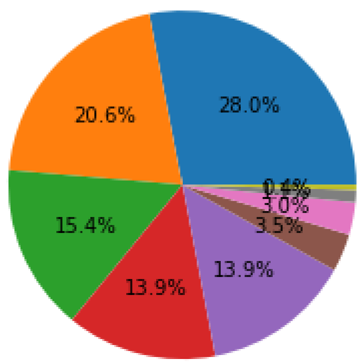
In [33]:
```
# taking a sample of 40,000
import random
df1 = new_df.sample(40000)
df1.shape
```

Out[33]: (40000, 11)

In [34]:
```
df1['label'].value_counts()
```

Out[34]:
```
1    11212
4     8254
7     6168
5     5575
6     5549
9     1404
8     1204
3      458
2      176
Name: label, dtype: int64
```

In [35]:
```
#distribution of sample df1
plt.pie(df1['label'].value_counts(), autopct = '%1.1f%%');
```



In [36]:
```
#importing libraries
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_auc_score
from sklearn.metrics import plot_roc_curve
from sklearn.model_selection import cross_val_score
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import f1_score
from sklearn.metrics import precision_score, recall_score

#for confusion matrix
import scikitplot as skplot

# for smote
import imblearn
from collections import Counter
from imblearn.over_sampling import SMOTE
```

Data Balancing using SMOTE : In order to cope with imbalanced data, there are 2 options :

Undersampling : Trim down the majority samples of the target variable.

Oversampling : Increase the minority samples of the target variable to the majority samples. we have decided to go with oversampling beacuse we might lose data if we do undersampling

For data balancing, we will use imblearn.

pip statement : !pip install imbalanced-learn

In [37]:
```
# Splitting x and y variables
x1 = df1[['time' ,'acc_x', 'mag_x', 'mag_y', 'acc_z', 'acc_y']] #independent feat
y1 = df1['label'] #dependent features
```

Taking only the 6 best features we got from chi2

In [38]:
```
print(x1.shape, y1.shape)
```

```
(40000, 6) (40000,)
```

In [39]:
```
#splitting the data
x1_train, x1_test, y1_train, y1_test = train_test_split(x1, y1, test_size = 0.3,
print(x1_train.shape, y1_train.shape, x1_test.shape)
print('Classes and number of values in trainset before SMOTE:',Counter(y1_train),

# applying smote to handle imbalance in the target variable
from imblearn.over_sampling import SMOTE
oversample = SMOTE()
x1_train,y1_train = oversample.fit_resample(x1_train,y1_train)
print('Classes and number of values in trainset after SMOTE:',Counter(y1_train),

# importing Logistic Regression
from sklearn.linear_model import LogisticRegression
classifier_lr = LogisticRegression(random_state = 1000, multi_class = 'multinomia

#fitting the logistic regression model to x1_train and y1_train
classifier_lr.fit(x1_train, y1_train)
y1_pred = classifier_lr.predict(x1_test)
print('model.predict :',y1_pred)
print('model.score :', classifier_lr.score(x1_train, y1_train))

#accuracy_score
from sklearn.metrics import accuracy_score
accuracy_lr = accuracy_score(y1_test, y1_pred)
print('Accuracy : ',accuracy_lr)

from sklearn.model_selection import cross_val_score
cv_scores_lr = cross_val_score(classifier_lr, x1, y1, cv=5)
print('Cross Validation scores :', cv_scores_lr)

mean_cv_lr = (np.mean(cv_scores_lr))*100
print('Mean cv :',mean_cv_lr)
```

```
(28000, 6) (28000,) (12000, 6)
Classes and number of values in trainset before SMOTE: Counter({1: 7831, 4: 578
2, 7: 4304, 5: 3913, 6: 3882, 9: 984, 8: 850, 3: 321, 2: 133})

Classes and number of values in trainset after SMOTE: Counter({4: 7831, 5: 783
1, 1: 7831, 7: 7831, 6: 7831, 8: 7831, 3: 7831, 9: 7831, 2: 7831})

model.predict : [2 1 4 ... 4 4 6]
model.score : 0.3597951162757701
Accuracy :  0.31875
Cross Validation scores : [0.419875 0.42225  0.429125 0.41875  0.422125]
Mean cv : 42.24249999999999
```

In [40]:
```
#f1_score
f1_score_lr = f1_score(y1_test, y1_pred, average='weighted')
print('F1-score (average = weighted): {:.2f}'.format(f1_score_lr))

#precision
precision_score_lr = precision_score(y1_test, y1_pred, average='weighted')
print('Precision (average = weighted): {:.2f}'.format(precision_score_lr))

#recall
recall_score_lr = recall_score(y1_test, y1_pred, average='weighted')
print('Recall (average = weighted): {:.2f}'.format(recall_score_lr))
```

```
F1-score (average = weighted): 0.33
Precision (average = weighted): 0.44
Recall (average = weighted): 0.32
```

1. F1 score average = 'weighted': Calculate metrics for each label, and find their average weighted by support (the number of true instances for each label). This alters ‘macro’ to account for label imbalance; it can result in an F-score that is not between precision and recall.
2. precison average = 'weighted' Calculate metrics for each label, and find their average weighted by support (the number of true instances for each label). This alters ‘macro’ to account for label imbalance; it can result in an F-score that is not between precision and recall.
3. recall average = 'weighted' Calculate metrics for each label, and find their average weighted by support (the number of true instances for each label). This alters ‘macro’ to account for label imbalance; it can result in an F-score that is not between precision and recall. Weighted recall is equal to accuracy.

Sample 2 - df2 - Decision Tree Classifier

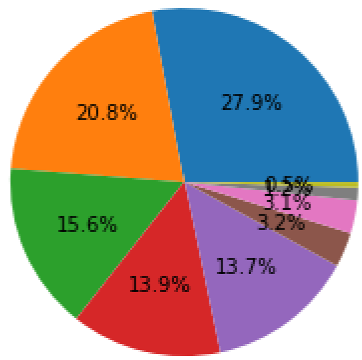
In [41]:
```
# taking a sample of 40,000
import random
df2 = new_df.sample(40000)
df2.shape
```

Out[41]:
```
(40000, 11)
```

In [42]:
```
df2['label'].value_counts()
```

Out[42]:
```
1    11172
4     8331
7     6244
6     5566
5     5494
9     1295
8     1227
3      474
2      197
Name: label, dtype: int64
```

In [43]:
```
#distribution of sample df2
plt.pie(df2['label'].value_counts(), autopct = '%1.1f%%');
```



In [44]:
```
# Splitting x and y variables
x2 = df2[['time' ,'acc_x', 'mag_x', 'mag_y', 'acc_z', 'acc_y']] #independent feat
y2 = df2['label'] #dependent features
print(x2.shape, y2.shape)
```

```
(40000, 6) (40000,)
```

In [45]:
```
#splitting the data
x2_train, x2_test, y2_train, y2_test = train_test_split(x2, y2, test_size = 0.3,
print(x2_train.shape, y2_train.shape, x2_test.shape)
print('Classes and number of values in trainset before SMOTE:',Counter(y2_train),

#smote
from imblearn.over_sampling import SMOTE
oversample = SMOTE()
x2_train,y2_train = oversample.fit_resample(x2_train,y2_train)
print('Classes and number of values in trainset after SMOTE:',Counter(y2_train),

#importing Decision Trees
from sklearn.tree import DecisionTreeClassifier
classifier_dtc = DecisionTreeClassifier(random_state=1000,max_depth=15,min_sample

classifier_dtc.fit(x2_train, y2_train)
y2_pred = classifier_dtc.predict(x2_test)
print('model.predict :',y2_pred)
print('model.score :', classifier_dtc.score(x2_train, y2_train))

from sklearn.metrics import accuracy_score
accuracy_dtc = accuracy_score(y2_test, y2_pred)
print('Accuracy : ',accuracy_dtc)

from sklearn.model_selection import cross_val_score
cv_scores_dtc = cross_val_score(classifier_dtc, x2, y2, cv=5)
print('Cross Validation scores :', cv_scores_dtc)

mean_cv_dtc = (np.mean(cv_scores_dtc))*100
print('Mean cv :',mean_cv_dtc)
```

```
(28000, 6) (28000,) (12000, 6)
Classes and number of values in trainset before SMOTE: Counter({1: 7876, 4: 581
7, 7: 4356, 6: 3877, 5: 3863, 9: 897, 8: 835, 3: 338, 2: 141})

Classes and number of values in trainset after SMOTE: Counter({1: 7876, 5: 787
6, 7: 7876, 4: 7876, 3: 7876, 6: 7876, 8: 7876, 9: 7876, 2: 7876})

model.predict : [1 4 1 ... 9 7 7]
model.score : 0.9457987698211162
Accuracy :  0.8805833333333334
Cross Validation scores : [0.939    0.933625 0.936375 0.93625  0.9395   ]
Mean cv : 93.69500000000001
```

In [46]:
```
f1_score_dtc = f1_score(y2_test, y2_pred, average='weighted')
print('F1-score (average = weighted): {:.2f}'.format(f1_score_dtc))

precision_score_dtc = precision_score(y2_test, y2_pred, average='weighted')
print('Precision (average = weighted): {:.2f}'.format(precision_score_dtc))

recall_score_dtc = recall_score(y2_test, y2_pred, average='weighted')
print('Recall (average = weighted): {:.2f}'.format(recall_score_dtc))
```

```
F1-score (average = weighted): 0.89
Precision (average = weighted): 0.90
Recall (average = weighted): 0.88
```

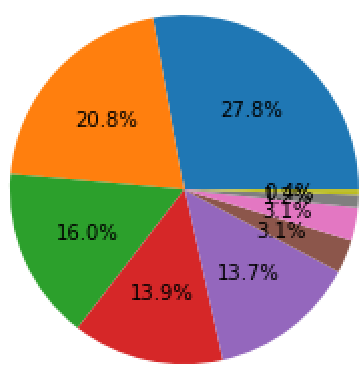
Sample 3 - df3 - Random Forest Classifier

In [47]:
```
import random
df3 = new_df.sample(40000)
```

In [48]:
```
df3['label'].value_counts()
```

Out[48]:
```
1    11128
4     8311
7     6381
5     5578
6     5498
8     1236
9     1231
3      469
2      168
Name: label, dtype: int64
```

In [75]:
```
#distribution of sample df3
plt.pie(df3['label'].value_counts(), autopct = '%1.1f%%');
```



In [49]:
```
# Splitting x and y variables
x3 = df3[['time' ,'acc_x', 'mag_x', 'mag_y', 'acc_z', 'acc_y']] #independent feat
y3 = df3['label'] #dependent features
print(x3.shape, y3.shape)
```

```
(40000, 6) (40000,)
```

In [50]:
```
#splitting the data
x3_train, x3_test, y3_train, y3_test = train_test_split(x3, y3, test_size = 0.3,
print('Classes and number of values in trainset before SMOTE:',Counter(y3_train),

#smote
from imblearn.over_sampling import SMOTE
oversample = SMOTE()
x3_train,y3_train = oversample.fit_resample(x3_train,y3_train)
print('Classes and number of values in trainset after SMOTE:',Counter(y3_train),

#import random forest
from sklearn.ensemble import RandomForestClassifier
classifier_rf = RandomForestClassifier(n_estimators=20, random_state=23)

classifier_rf.fit(x3_train, y3_train)
y3_pred = classifier_rf.predict(x3_test)
print('model.predict :',y3_pred)
print('model.score :', classifier_rf.score(x3_train, y3_train))

from sklearn.metrics import accuracy_score
accuracy_rf = accuracy_score(y3_test, y3_pred)
print('Accuracy : ',accuracy_rf)

from sklearn.model_selection import cross_val_score
cv_scores_rf = cross_val_score(classifier_rf, x3, y3, cv=5)
print('Cross Validation scores :', cv_scores_rf)

mean_accuracy_rf = (np.mean(cv_scores_rf))*100
print('Mean Accuracy :',mean_accuracy_rf)
```

```
Classes and number of values in trainset before SMOTE: Counter({1: 7823, 4: 583
9, 7: 4488, 5: 3878, 6: 3823, 8: 876, 9: 848, 3: 311, 2: 114})

Classes and number of values in trainset after SMOTE: Counter({9: 7823, 7: 782
3, 6: 7823, 4: 7823, 5: 7823, 1: 7823, 8: 7823, 3: 7823, 2: 7823})

model.predict : [8 4 5 ... 4 4 4]
model.score : 0.9998721718010993
Accuracy :  0.92075
Cross Validation scores : [0.936875 0.937125 0.94125  0.94425  0.9305   ]
Mean Accuracy : 93.80000000000001
```

In [51]:
```
f1_score_rf = f1_score(y3_test, y3_pred, average='weighted')
print('F1-score (average = weighted): {:.2f}'.format(f1_score_rf))

precision_score_rf = precision_score(y3_test, y3_pred, average='weighted')
print('Precision (average = weighted): {:.2f}'.format(precision_score_rf))

recall_score_rf = recall_score(y3_test, y3_pred, average='weighted')
print('Recall (average = weighted): {:.2f}'.format(recall_score_rf))
```

```
F1-score (average = weighted): 0.92
Precision (average = weighted): 0.92
Recall (average = weighted): 0.92
```

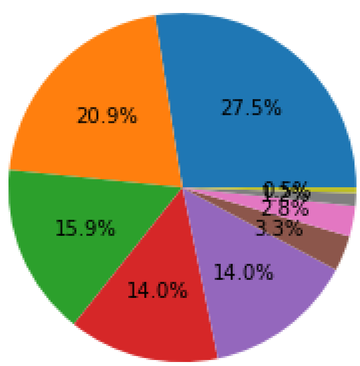
Sample 4 - df4 - Support Vector Classifier

In [52]:
```
import random
df4 = new_df.sample(40000)
```

In [53]:
```
df4['label'].value_counts()
```

Out[53]:
```
1    10993
4     8368
7     6357
6     5586
5     5580
9     1320
8     1129
3      482
2      185
Name: label, dtype: int64
```

In [76]:
```
#distribution of sample df4
plt.pie(df4['label'].value_counts(), autopct = '%1.1f%%');
```



In [54]:
```
# Splitting x and y variables
x4 = df4[['time' ,'acc_x', 'mag_x', 'mag_y', 'acc_z', 'acc_y']] #independent feat
y4 = df4['label'] #dependent features
print(x4.shape, y4.shape)
```

```
(40000, 6) (40000,)
```

In [55]:
```
#splitting the data
x4_train, x4_test, y4_train, y4_test = train_test_split(x4, y4, test_size = 0.3,
print('Classes and number of values in trainset before SMOTE:',Counter(y4_train),

#smote
from imblearn.over_sampling import SMOTE
oversample = SMOTE()
x4_train,y4_train = oversample.fit_resample(x4_train,y4_train)
print('Classes and number of values in trainset after SMOTE:',Counter(y4_train),

#importing svc
from sklearn.svm import SVC
classifier_svc=SVC(decision_function_shape='ovo')


classifier_svc.fit(x4_train, y4_train)
y4_pred = classifier_svc.predict(x4_test)
print('model.predict :',y4_pred)
print('model.score :', classifier_svc.score(x4_train, y4_train))

from sklearn.metrics import accuracy_score
accuracy_svc = accuracy_score(y4_test, y4_pred)
print('Accuracy : ',accuracy_svc)

from sklearn.model_selection import cross_val_score
cv_scores_svc = cross_val_score(classifier_svc, x4, y4, cv=5)
print('Cross Validation scores :', cv_scores_svc)

mean_cv_svc = (np.mean(cv_scores_svc))*100
print('Mean cv :',mean_cv_svc)
```

```
Classes and number of values in trainset before SMOTE: Counter({1: 7670, 4: 586
6, 7: 4485, 5: 3906, 6: 3892, 9: 925, 8: 783, 3: 339, 2: 134})

Classes and number of values in trainset after SMOTE: Counter({1: 7670, 4: 767
0, 7: 7670, 6: 7670, 8: 7670, 5: 7670, 9: 7670, 2: 7670, 3: 7670})

model.predict : [1 5 9 ... 1 8 5]
model.score : 0.7504852962480081
Accuracy :  0.6705833333333333
Cross Validation scores : [0.722    0.707375 0.7115   0.716375 0.712125]
Mean cv : 71.38749999999999
```

In [56]:
```
f1_score_svc = f1_score(y4_test, y4_pred, average='weighted')
print('F1-score (average = weighted): {:.2f}'.format(f1_score_svc))

precision_score_svc = precision_score(y4_test, y4_pred, average='weighted')
print('Precision (average = weighted): {:.2f}'.format(precision_score_svc))

recall_score_svc = recall_score(y4_test, y4_pred, average='weighted')
print('Recall (average = weighted): {:.2f}'.format(recall_score_svc))
```

```
F1-score (average = weighted): 0.68
Precision (average = weighted): 0.71
Recall (average = weighted): 0.67
```

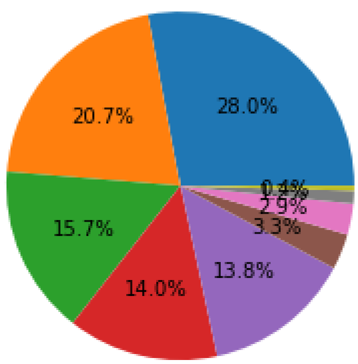
Sample 5 - df5 - KNearest Neighbors

In [57]:
```
import random
df5 = new_df.sample(40000)
```

In [58]:
```
df5['label'].value_counts()
```

Out[58]:
```
1    11185
4     8300
7     6278
5     5590
6     5524
9     1323
8     1154
3      479
2      167
Name: label, dtype: int64
```

In [77]:
```
#distribution of sample df5
plt.pie(df5['label'].value_counts(), autopct = '%1.1f%%');
```



In [59]:
```
# Splitting x and y variables
x5 = df5[['time' ,'acc_x', 'mag_x', 'mag_y', 'acc_z', 'acc_y']] #independent feat
y5 = df5['label'] #dependent features
```

In [60]:
```
#splitting the data
x5_train, x5_test, y5_train, y5_test = train_test_split(x5, y5, test_size = 0.3,
print('Classes and number of values in trainset before SMOTE:',Counter(y5_train),

#smote
from imblearn.over_sampling import SMOTE
oversample = SMOTE()
x5_train,y5_train = oversample.fit_resample(x5_train,y5_train)
print('Classes and number of values in trainset after SMOTE:',Counter(y5_train),

#importing kneighbours classifier
from sklearn.neighbors import KNeighborsClassifier
classifier_knn= KNeighborsClassifier()

classifier_knn.fit(x5_train, y5_train)
y5_pred = classifier_knn.predict(x5_test)
print('model.predict :',y5_pred)
print('model.score :', classifier_knn.score(x5_train, y5_train))

from sklearn.metrics import accuracy_score
accuracy_knn = accuracy_score(y5_test, y5_pred)
print('Accuracy : ',accuracy_knn)

from sklearn.model_selection import cross_val_score
cv_scores_knn = cross_val_score(classifier_knn, x5, y5, cv=5)
print('Cross Validation scores :', cv_scores_knn)

mean_cv_knn = (np.mean(cv_scores_knn))*100
print('Mean cv :',mean_cv_knn)
```

```
Classes and number of values in trainset before SMOTE: Counter({1: 7786, 4: 574
9, 7: 4420, 5: 3974, 6: 3912, 9: 921, 8: 784, 3: 328, 2: 126})

Classes and number of values in trainset after SMOTE: Counter({4: 7786, 7: 778
6, 6: 7786, 1: 7786, 2: 7786, 5: 7786, 3: 7786, 9: 7786, 8: 7786})

model.predict : [9 7 8 ... 5 7 1]
model.score : 0.9373091303479l8
Accuracy :  0.7680833333333333
Cross Validation scores : [0.7995   0.79975  0.79275  0.803375 0.7985   ]
Mean cv : 79.8775
```

In [61]:
```
f1_score_knn = f1_score(y5_test, y5_pred, average='weighted')
print('F1-score (average = weighted): {:.2f}'.format(f1_score_knn))

precision_score_knn = precision_score(y5_test, y5_pred, average='weighted')
print('Precision (average = weighted): {:.2f}'.format(precision_score_knn))

recall_score_knn = recall_score(y5_test, y5_pred, average='weighted')
print('Recall (average = weighted): {:.2f}'.format(recall_score_knn))
```

```
F1-score (average = weighted): 0.78
Precision (average = weighted): 0.79
Recall (average = weighted): 0.77
```

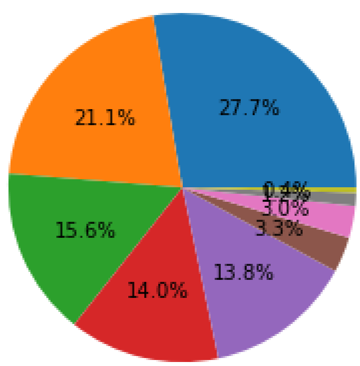
Sample 6 - df6 - AdaBoost Classifier

In [62]:
```
import random
df6 = new_df.sample(40000)
```

In [63]:
```
df6['label'].value_counts()
```

Out[63]:
```
1    11071
4     8423
7     6240
6     5588
5     5512
9     1322
8     1180
3      489
2      175
Name: label, dtype: int64
```

In [78]:
```
#distribution of sample df6
plt.pie(df6['label'].value_counts(), autopct = '%1.1f%%');
```



In [64]:
```
# Splitting x and y variables
x6 = df6[['time' ,'acc_x', 'mag_x', 'mag_y', 'acc_z', 'acc_y']] #independent feat
y6 = df6['label'] #dependent features
```

In [65]:
```
###### splitting the data
x6_train, x6_test, y6_train, y6_test = train_test_split(x6, y6, test_size = 0.3,
print('Classes and number of values in trainset before SMOTE:',Counter(y6_train),

#smote
from imblearn.over_sampling import SMOTE
oversample = SMOTE()
x6_train,y6_train = oversample.fit_resample(x6_train,y6_train)
print('Classes and number of values in trainset after SMOTE:',Counter(y6_train),'


from sklearn.ensemble import AdaBoostClassifier
classifier_ada = AdaBoostClassifier()

classifier_ada.fit(x6_train, y6_train)
y6_pred = classifier_ada.predict(x6_test)
print('model.predict :',y6_pred)
print('model.score :', classifier_ada.score(x6_train, y6_train))

from sklearn.metrics import accuracy_score
accuracy_ada = accuracy_score(y6_test, y6_pred)
print('Accuracy : ',accuracy_ada)

from sklearn.model_selection import cross_val_score
cv_scores_ada = cross_val_score(classifier_ada, x6, y6, cv=5)
print('Cross Validation scores :', cv_scores_ada)

mean_cv_ada = (np.mean(cv_scores_ada))*100
print('Mean cv :',mean_cv_ada)
```

```
Classes and number of values in trainset before SMOTE: Counter({1: 7668, 4: 589
0, 7: 4386, 5: 3913, 6: 3897, 9: 942, 8: 812, 3: 361, 2: 131})

Classes and number of values in trainset after SMOTE: Counter({7: 7668, 1: 766
8, 6: 7668, 4: 7668, 2: 7668, 5: 7668, 8: 7668, 3: 7668, 9: 7668})

model.predict : [1 5 4 ... 9 5 7]
model.score : 0.43169303889178695
Accuracy :  0.40108333333333335
Cross Validation scores : [0.4045   0.471625 0.52675  0.5295   0.50475 ]
Mean cv : 48.7425
```

In [66]:
```
f1_score_ada = f1_score(y6_test, y6_pred, average='weighted')
print('F1-score (average = weighted): {:.2f}'.format(f1_score_ada))

precision_score_ada = precision_score(y6_test, y6_pred, average='weighted')
print('Precision (average = weighted): {:.2f}'.format(precision_score_ada))

recall_score_ada = recall_score(y6_test, y6_pred, average='weighted')
print('Recall (average = weighted): {:.2f}'.format(recall_score_ada))
```

```
F1-score (average = weighted): 0.43
Precision (average = weighted): 0.51
Recall (average = weighted): 0.40
```

MAKING A DATAFRAME OF ALL THE SCORES FOR EVERY MODEL BUILT

In [85]:
```
#Making a dataframe of all the scores for every model
scores = [("Logistic Regression", accuracy_lr,mean_cv_lr, f1_score_lr,precision_s
           ("Decision Tree",accuracy_dtc,mean_cv_dtc, f1_score_dtc,precision_scor
           ("Random Forest", accuracy_rf,mean_accuracy_rf, f1_score_rf,precision_
           ("KNN", accuracy_knn,mean_cv_knn, f1_score_knn,precision_score_knn,rec
           ('Support vector machine',accuracy_svc,mean_cv_svc, f1_score_svc,preci
           ('AdaBoost Classifier',accuracy_ada,mean_cv_ada, f1_score_ada,precisic

Scores =pd.DataFrame(data = scores, columns=['Model Name','Test Accuracy','Mean C
Scores.set_index('Model Name', inplace = True)
```

In [86]:
```
Scores.style.background_gradient(cmap='YlGn')
```

Out[86]:

Model Name	Test Accuracy	Mean Cross validation score	F1 Score	Precision	Recall
Logistic Regression	0.318750	42.242500	0.327531	0.441404	0.318750
Decision Tree	0.880583	93.695000	0.885856	0.895144	0.880583
Random Forest	0.920750	93.800000	0.921957	0.923867	0.920750
KNN	0.768083	79.877500	0.775313	0.788165	0.768083
Support vector machine	0.670583	71.387500	0.684214	0.712492	0.670583
AdaBoost Classifier	0.401083	48.742500	0.425586	0.508722	0.401083

Conclusion:

We see that Random Forest gives the highest accuracy.

In [ ]: