Assignment-13 - [KNN] - GLASS

In [181]:
```
#KNN Classification
import pandas as pd
import numpy as np
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [182]:
```
glass = pd.read_csv('glass.csv')
```

In [183]:
```
glass
```

Out[183]:

	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe	Type
0	1.52101	13.64	4.49	1.10	71.78	0.06	8.75	0.00	0.0	1
1	1.51761	13.89	3.60	1.36	72.73	0.48	7.83	0.00	0.0	1
2	1.51618	13.53	3.55	1.54	72.99	0.39	7.78	0.00	0.0	1
3	1.51766	13.21	3.69	1.29	72.61	0.57	8.22	0.00	0.0	1
4	1.51742	13.27	3.62	1.24	73.08	0.55	8.07	0.00	0.0	1
...	...	...	...	...	...	...	...	...	...	...
209	1.51623	14.14	0.00	2.88	72.61	0.08	9.18	1.06	0.0	7
210	1.51685	14.92	0.00	1.99	73.06	0.00	8.40	1.59	0.0	7
211	1.52065	14.36	0.00	2.02	73.42	0.00	8.44	1.64	0.0	7
212	1.51651	14.38	0.00	1.94	73.61	0.00	8.48	1.57	0.0	7
213	1.51711	14.23	0.00	2.08	73.36	0.00	8.62	1.67	0.0	7

214 rows × 10 columns

In [184]:
```
glass['Type'].value_counts()
```

Out[184]:
```
2    76
1    70
7    29
3    17
5    13
6     9
Name: Type, dtype: int64
```

In [185]:
```
glass.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 214 entries, 0 to 213
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   RI      214 non-null    float64
 1   Na      214 non-null    float64
 2   Mg      214 non-null    float64
 3   Al      214 non-null    float64
 4   Si      214 non-null    float64
 5   K       214 non-null    float64
 6   Ca      214 non-null    float64
 7   Ba      214 non-null    float64
 8   Fe      214 non-null    float64
 9   Type    214 non-null    int64  
dtypes: float64(9), int64(1)
memory usage: 16.8 KB
```

In [186]:
```
glass.describe()
```

Out[186]:

	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe	Type
count	214.000000	214.000000	214.000000	214.000000	214.000000	214.000000	214.000000	214.000000	214.000000	214.000000
mean	1.518365	13.407850	2.684533	1.444907	72.650935	0.497056	8.956963	0.175047	0.057009	2.780374
std	0.003037	0.816604	1.442408	0.499270	0.774546	0.652192	1.423153	0.497219	0.097439	2.103739
min	1.511150	10.730000	0.000000	0.290000	69.810000	0.000000	5.430000	0.000000	0.000000	1.000000
25%	1.516522	12.907500	2.115000	1.190000	72.280000	0.122500	8.240000	0.000000	0.000000	1.000000
50%	1.517680	13.300000	3.480000	1.360000	72.790000	0.555000	8.600000	0.000000	0.000000	2.000000
75%	1.519157	13.825000	3.600000	1.630000	73.087500	0.610000	9.172500	0.000000	0.100000	3.000000
max	1.533930	17.380000	4.490000	3.500000	75.410000	6.210000	16.190000	3.150000	0.510000	7.000000

In [187]:
```
glass[glass.duplicated()].shape
```

Out[187]: (1, 10)

In [188]:
```
glass[glass.duplicated()]
```

Out[188]:

	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe	Type
39	1.52213	14.21	3.82	0.47	71.77	0.11	9.57	0.0	0.0	1

In [189]:
```
df = glass.drop_duplicates()
```

In [190]:
```
df
```

Out[190]:

	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe	Type
0	1.52101	13.64	4.49	1.10	71.78	0.06	8.75	0.00	0.0	1
1	1.51761	13.89	3.60	1.36	72.73	0.48	7.83	0.00	0.0	1
2	1.51618	13.53	3.55	1.54	72.99	0.39	7.78	0.00	0.0	1
3	1.51766	13.21	3.69	1.29	72.61	0.57	8.22	0.00	0.0	1
4	1.51742	13.27	3.62	1.24	73.08	0.55	8.07	0.00	0.0	1
...	...	...	...	...	...	...	...	...	...	...
209	1.51623	14.14	0.00	2.88	72.61	0.08	9.18	1.06	0.0	7
210	1.51685	14.92	0.00	1.99	73.06	0.00	8.40	1.59	0.0	7
211	1.52065	14.36	0.00	2.02	73.42	0.00	8.44	1.64	0.0	7
212	1.51651	14.38	0.00	1.94	73.61	0.00	8.48	1.57	0.0	7
213	1.51711	14.23	0.00	2.08	73.36	0.00	8.62	1.67	0.0	7

213 rows × 10 columns

In [191]:
```
corr = df.corr()
```

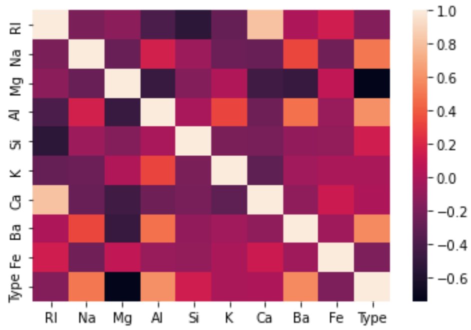
In [192]:
```
corr
```

Out[192]:

	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe	Type
RI	1.000000	-0.198802	-0.127526	-0.400973	-0.539000	-0.287645	0.811183	0.001679	0.147083	-0.160140
Na	-0.198802	1.000000	-0.278420	0.167735	-0.064885	-0.264158	-0.278194	0.329080	-0.239374	0.508837
Mg	-0.127526	-0.278420	1.000000	-0.479575	-0.162437	0.007617	-0.446197	-0.491818	0.085426	-0.744195
Al	-0.400973	0.167735	-0.479575	1.000000	-0.016195	0.323683	-0.258068	0.480642	-0.080583	0.597432
Si	-0.539000	-0.064885	-0.162437	-0.016195	1.000000	-0.197281	-0.207145	-0.104389	-0.097717	0.147725
K	-0.287645	-0.264158	0.007617	0.323683	-0.197281	1.000000	-0.317032	-0.043653	-0.009372	-0.012455
Ca	0.811183	-0.278194	-0.446197	-0.258068	-0.207145	-0.317032	1.000000	-0.112208	0.126314	0.002677
Ba	0.001679	0.329080	-0.491818	0.480642	-0.104389	-0.043653	-0.112208	1.000000	-0.059729	0.574896
Fe	0.147083	-0.239374	0.085426	-0.080583	-0.097717	-0.009372	0.126314	-0.059729	1.000000	-0.191090
Type	-0.160140	0.508837	-0.744195	0.597432	0.147725	-0.012455	0.002677	0.574896	-0.191090	1.000000

In [193]:
```
sns.heatmap(corr)
```

Out[193]: <AxesSubplot:>

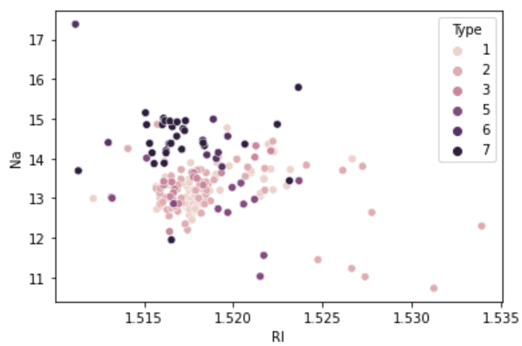


In [194]:
```
# We can notice that Ca and K values don't affect type that much.

# Also Ca and RI are highly correlated, this means using only RI is enough.

# So we can go ahead and drop Ca, and also K.(Performed later)
```

Scatter plot of two features, and pairwise plot

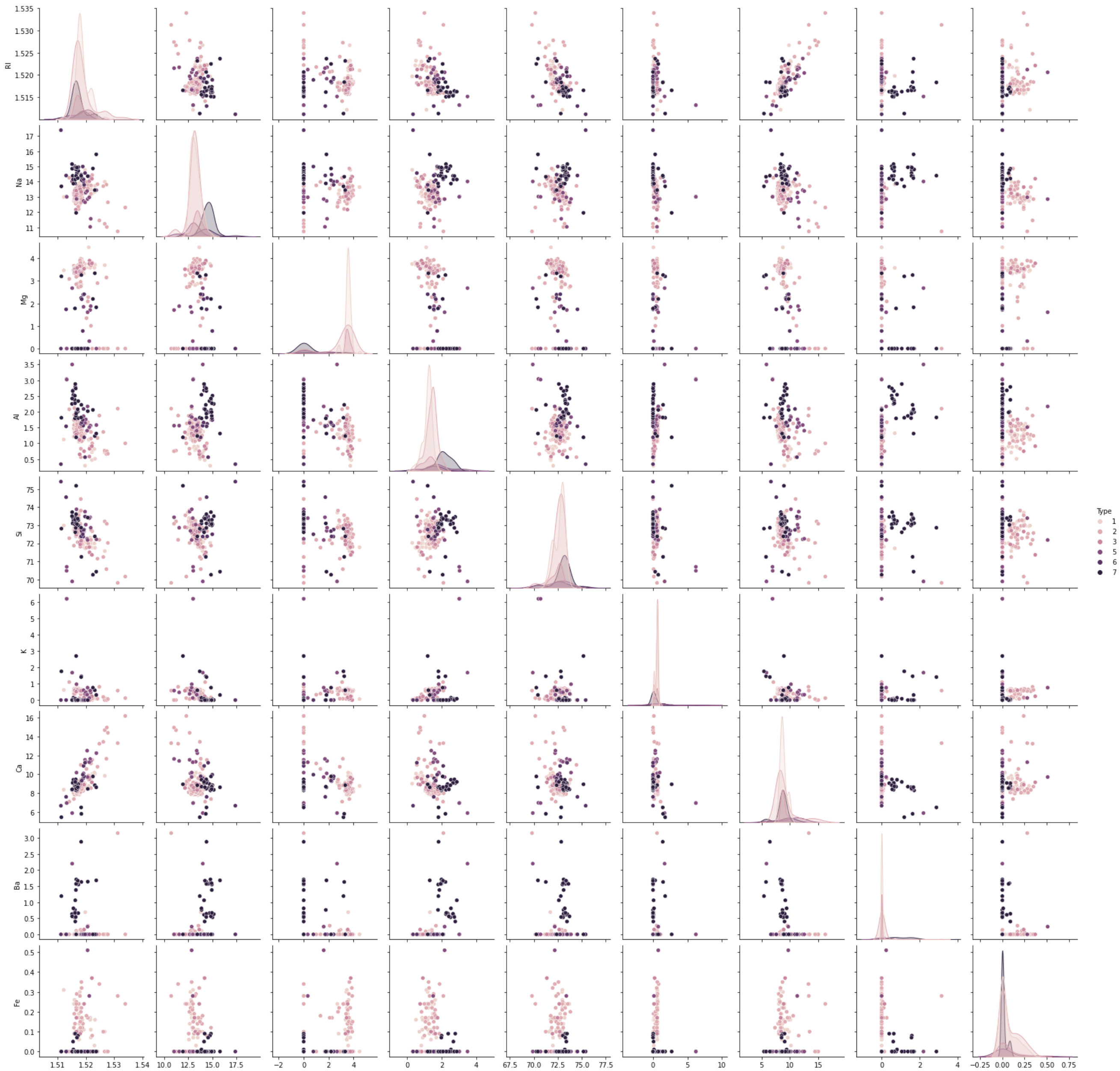
In [195]:
```
sns.scatterplot(df['RI'],df['Na'],hue=df['Type'])
```

Out[195]: <AxesSubplot:xlabel='RI', ylabel='Na'>



In [196]:
```
# Suppose we consider only RI, and Na values for classification for glass type.

#From the above plot, We first calculate the nearest neighbors from the new data point to be calculated.
#If the majority of nearest neighbors belong to a particular class, say type 4, then we classify the data point as type 4.
#But there are a lot more than two features based on which we can classify. So let us take a look at pairwise plot to captur
```

In [197]:
```
#pairwise plot of all the features
sns.pairplot(df,hue='Type')
plt.show()
```



In [198]:
```
##The pairplot shows that the data is not linear and KNN can be applied to get nearest neighbors and clasify the glass types
```

In [199]:
```
df
```

Out[199]:

	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe	Type
0	1.52101	13.64	4.49	1.10	71.78	0.06	8.75	0.00	0.0	1
1	1.51761	13.89	3.60	1.36	72.73	0.48	7.83	0.00	0.0	1
2	1.51618	13.53	3.55	1.54	72.99	0.39	7.78	0.00	0.0	1
3	1.51766	13.21	3.69	1.29	72.61	0.57	8.22	0.00	0.0	1
4	1.51742	13.27	3.62	1.24	73.08	0.55	8.07	0.00	0.0	1
...	...	...	...	...	...	...	...	...	...	...
209	1.51623	14.14	0.00	2.88	72.61	0.08	9.18	1.06	0.0	7
210	1.51685	14.92	0.00	1.99	73.06	0.00	8.40	1.59	0.0	7
211	1.52065	14.36	0.00	2.02	73.42	0.00	8.44	1.64	0.0	7
212	1.51651	14.38	0.00	1.94	73.61	0.00	8.48	1.57	0.0	7
213	1.51711	14.23	0.00	2.08	73.36	0.00	8.62	1.67	0.0	7

213 rows × 10 columns

Feature scaling

In [200]:
```
DF = df.iloc[:,0:9]
```

In [201]:
```
DF
```

Out[201]:

	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe
0	1.52101	13.64	4.49	1.10	71.78	0.06	8.75	0.00	0.0
1	1.51761	13.89	3.60	1.36	72.73	0.48	7.83	0.00	0.0
2	1.51618	13.53	3.55	1.54	72.99	0.39	7.78	0.00	0.0
3	1.51766	13.21	3.69	1.29	72.61	0.57	8.22	0.00	0.0
4	1.51742	13.27	3.62	1.24	73.08	0.55	8.07	0.00	0.0
...	...	...	...	...	...	...	...	...	...
209	1.51623	14.14	0.00	2.88	72.61	0.08	9.18	1.06	0.0
210	1.51685	14.92	0.00	1.99	73.06	0.00	8.40	1.59	0.0
211	1.52065	14.36	0.00	2.02	73.42	0.00	8.44	1.64	0.0
212	1.51651	14.38	0.00	1.94	73.61	0.00	8.48	1.57	0.0
213	1.51711	14.23	0.00	2.08	73.36	0.00	8.62	1.67	0.0

213 rows × 9 columns

In [202]:
```
array= DF.values
```

In [203]:
```
array
```

Out[203]:
```
array([[ 1.52101, 13.64   ,  4.49   , ...,  8.75   ,  0.     ,  0.     ],
       [ 1.51761, 13.89   ,  3.6    , ...,  7.83   ,  0.     ,  0.     ],
       [ 1.51618, 13.53   ,  3.55   , ...,  7.78   ,  0.     ,  0.     ],
       ...,
       [ 1.52065, 14.36   ,  0.     , ...,  8.44   ,  1.64   ,  0.     ],
       [ 1.51651, 14.38   ,  0.     , ...,  8.48   ,  1.57   ,  0.     ],
       [ 1.51711, 14.23   ,  0.     , ...,  8.62   ,  1.67   ,  0.     ]])
```

In [204]:
```
from sklearn.preprocessing import StandardScaler
```

In [205]:
```
# Normalization function
stscaler = StandardScaler().fit(array)
X = stscaler.transform(array)
```

In [206]:
```
X
```

Out[206]:
```
array([[ 0.87984017,  0.28955813,  1.25723832, ..., -0.14346582,
        -0.35380764, -0.58830108],
       [-0.24381562,  0.59640332,  0.63931074, ..., -0.79020061,
        -0.35380764, -0.58830108],
       [-0.71641202,  0.15454625,  0.6045957 , ..., -0.82534924,
        -0.35380764, -0.58830108],
       ...,
       [ 0.76086485,  1.17327228, -1.86017161, ..., -0.36138732,
         2.94550057, -0.58830108],
       [-0.60735132,  1.19781989, -1.86017161, ..., -0.33326842,
         2.80467644, -0.58830108],
       [-0.40905912,  1.01371278, -1.86017161, ..., -0.23485225,
         3.00585377, -0.58830108]])
```

In [207]:
```
df_knn = pd.DataFrame(X,columns=df.columns[:-1])
```

In [208]:
```
df_knn
```

Out[208]:

	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe
0	0.879840	0.289558	1.257238	-0.706370	-1.133248	-0.673480	-0.143466	-0.353808	-0.588301
1	-0.243816	0.596403	0.639311	-0.180863	0.097037	-0.028962	-0.790201	-0.353808	-0.588301
2	-0.716412	0.154546	0.604596	0.182950	0.433746	-0.167073	-0.825349	-0.353808	-0.588301
3	-0.227291	-0.238216	0.701798	-0.322346	-0.058368	0.109149	-0.516041	-0.353808	-0.588301
4	-0.306608	-0.164573	0.653197	-0.423405	0.550299	0.078457	-0.621487	-0.353808	-0.588301
...	...	...	...	...	...	...	...	...	...
208	-0.699888	0.903249	-1.860172	2.891336	-0.058368	-0.642789	0.158812	1.778672	-0.588301
209	-0.494986	1.860605	-1.860172	1.092483	0.524398	-0.765554	-0.389506	2.844912	-0.588301
210	0.760865	1.173272	-1.860172	1.153118	0.990612	-0.765554	-0.361387	2.945501	-0.588301
211	-0.607351	1.197820	-1.860172	0.991424	1.236668	-0.765554	-0.333268	2.804676	-0.588301
212	-0.409059	1.013713	-1.860172	1.274389	0.912909	-0.765554	-0.234852	3.005854	-0.588301

213 rows × 9 columns

In [209]:
```
x= df_knn
y= df['Type']
```

In [210]:
```
x
```

Out[210]:

	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe
0	0.879840	0.289558	1.257238	-0.706370	-1.133248	-0.673480	-0.143466	-0.353808	-0.588301
1	-0.243816	0.596403	0.639311	-0.180863	0.097037	-0.028962	-0.790201	-0.353808	-0.588301
2	-0.716412	0.154546	0.604596	0.182950	0.433746	-0.167073	-0.825349	-0.353808	-0.588301
3	-0.227291	-0.238216	0.701798	-0.322346	-0.058368	0.109149	-0.516041	-0.353808	-0.588301
4	-0.306608	-0.164573	0.653197	-0.423405	0.550299	0.078457	-0.621487	-0.353808	-0.588301
...	...	...	...	...	...	...	...	...	...
208	-0.699888	0.903249	-1.860172	2.891336	-0.058368	-0.642789	0.158812	1.778672	-0.588301
209	-0.494986	1.860605	-1.860172	1.092483	0.524398	-0.765554	-0.389506	2.844912	-0.588301
210	0.760865	1.173272	-1.860172	1.153118	0.990612	-0.765554	-0.361387	2.945501	-0.588301
211	-0.607351	1.197820	-1.860172	0.991424	1.236668	-0.765554	-0.333268	2.804676	-0.588301
212	-0.409059	1.013713	-1.860172	1.274389	0.912909	-0.765554	-0.234852	3.005854	-0.588301

213 rows × 9 columns

In [211]:
```
y
```

Out[211]:
```
0      1
1      1
2      1
3      1
4      1
      ..
209    7
210    7
211    7
212    7
213    7
Name: Type, Length: 213, dtype: int64
```

In [212]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test= train_test_split(x,y, test_size=0.3,random_state=45)
```

In [213]:
```
x_train
```

Out[213]:

	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe
185	0.010659	1.124177	0.403249	1.557355	-1.819617	1.474913	-2.224265	2.925383	-0.588301
202	-0.584217	1.713320	-1.860172	1.092483	0.589150	-0.765554	-0.473863	3.086325	-0.588301
210	0.760865	1.173272	-1.860172	1.153118	0.990612	-0.765554	-0.361387	2.945501	-0.588301
72	-0.673449	-0.078656	0.618482	0.243586	0.278342	0.170531	-0.748022	-0.353808	-0.588301
58	-0.266950	-0.017287	0.680969	-0.524464	0.174739	0.109149	-0.480893	-0.353808	0.541526
...	...	...	...	...	...	...	...	...	...
32	-0.197547	-0.680073	0.555995	-0.443617	0.407845	0.170531	-0.277031	-0.172748	1.671354
124	0.123025	-0.581882	0.680969	0.223374	-0.187871	0.124494	-0.284060	-0.353808	0.644238
131	-0.071962	0.031808	0.903145	-0.544676	-0.213772	0.124494	-0.565249	-0.353808	-0.588301
158	-0.128145	0.117725	0.472679	0.364857	-0.926042	0.109149	-0.101287	-0.353808	0.336103
203	-0.719717	1.897427	-1.860172	1.658414	0.835207	-0.765554	-0.171585	0.994080	-0.588301

149 rows × 9 columns

In [214]:
```
x_test
```

Out[214]:

	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe
83	-1.407130	1.038260	0.285217	1.274389	-0.485730	0.922469	-1.317430	-0.353808	-0.588301
62	1.296254	0.940070	0.785114	-1.353149	-1.690113	-0.765554	0.517328	-0.353808	-0.588301
84	-0.693278	-0.054108	0.625425	0.081891	0.084086	-0.074999	-0.523071	-0.353808	-0.588301
137	-0.531339	-0.753716	0.583767	0.182950	0.912909	0.247260	-0.740993	-0.353808	-0.588301
187	1.362351	1.786963	-0.332710	1.233966	-3.101703	0.400716	0.566537	-0.353808	-0.588301
...	...	...	...	...	...	...	...	...	...
115	-0.019084	-0.201394	0.847601	-0.079804	-0.420978	0.078457	-0.452774	-0.353808	0.438815
4	-0.306608	-0.164573	0.653197	-0.423405	0.550299	0.078457	-0.621487	-0.353808	-0.588301
28	-0.220682	-1.036013	0.583767	-0.039380	0.640952	0.109149	-0.291090	-0.353808	-0.588301
113	0.040403	-0.373227	0.896202	-0.524464	-0.278524	0.155186	-0.368417	-0.353808	-0.588301
125	-0.554473	-0.569608	0.646254	-0.382981	0.122937	0.093803	-0.248912	-0.353808	-0.588301

64 rows × 9 columns

In [215]:
```
y_train
```

Out[215]:
```
186    7
203    7
211    7
73     2
59     1
      ..
32     1
125    2
132    2
159    3
204    7
Name: Type, Length: 149, dtype: int64
```

In [216]:
```
y_test
```

Out[216]:
```
84     2
63     1
85     2
138    2
188    7
      ..
116    2
4      1
28     1
114    2
126    2
Name: Type, Length: 64, dtype: int64
```

KNN Model

In [217]:
```
model = KNeighborsClassifier(n_neighbors=3)
model.fit(x_train,y_train)
```

Out[217]:
```
KNeighborsClassifier(n_neighbors=3)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [218]:
```
# Predicting on testdata
preds = model.predict(x_test) #Prediciting on test data set
pd.Series(preds).value_counts() #Getting the count of each category
```

Out[218]:
```
1    29
2    23
7     7
3     3
5     2
dtype: int64
```

In [219]:
```
pd.crosstab(y_test,preds)  #Getting the 2 way table to understand the correct and wrong predictions
```

Out[219]:

col_0	1	2	3	5	7
Type					
1	16	2	1	0	0
2	6	19	2	1	0
3	6	2	0	0	0
7	1	0	0	1	7

In [220]:
```
print("Accuracy", accuracy_score(y_test,preds)*100)
```

```
Accuracy 65.625
```

In [221]:
```
model.score(x_train,y_train)
```

Out[221]:
```
0.825503355704698
```

In [222]:
```
# Classification mertices
from sklearn.metrics import classification_report
```

In [223]:
```
print(classification_report(y_test,preds))
```

```
              precision    recall  f1-score   support

           1       0.55      0.84      0.67        19
           2       0.83      0.68      0.75        28
           3       0.00      0.00      0.00         8
           5       0.00      0.00      0.00         0
           7       1.00      0.78      0.88         9

    accuracy                           0.66        64
   macro avg       0.48      0.46      0.46        64
weighted avg       0.67      0.66      0.65        64
```

Grid search for Algorithm Tuning

In [224]:
```
n_neighbors = np.array(range(1,15))
param_grid = dict(n_neighbors=n_neighbors)
```

In [225]:
```
model = KNeighborsClassifier()
grid = GridSearchCV(estimator=model, param_grid=param_grid)
grid.fit(x, y)
```

Out[225]:
```
GridSearchCV(estimator=KNeighborsClassifier(),
             param_grid={'n_neighbors': array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14])})
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [226]:

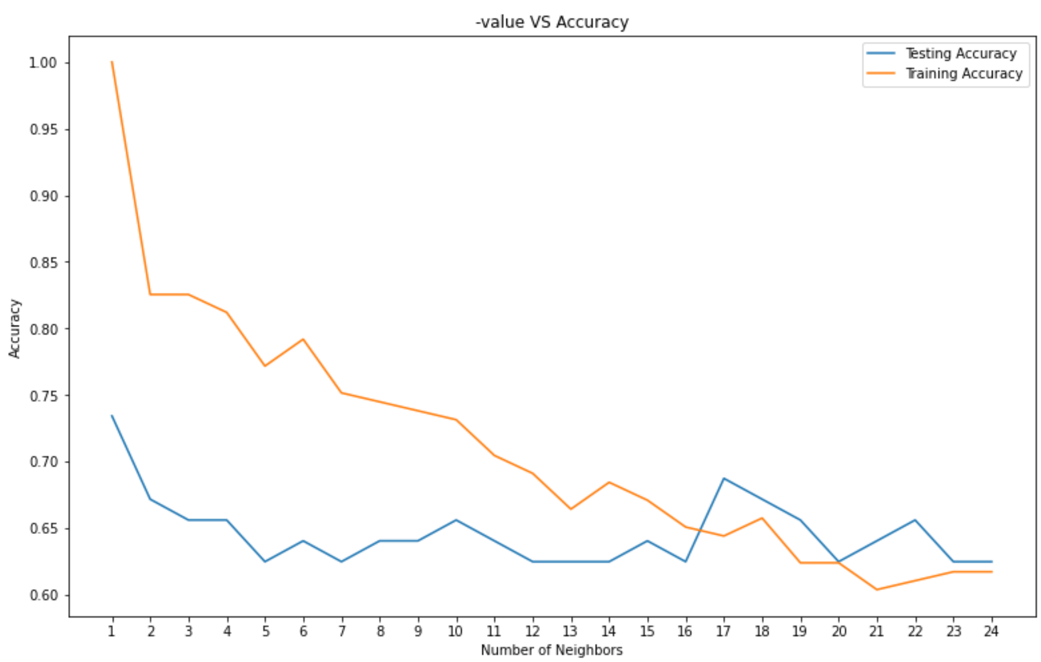
```
print(grid.best_score_)
print(grid.best_params_)
```

```
0.6666666666666667
{'n_neighbors': 2}
```

Visualizing the CV

In [227]:

```
k_values = np.arange(1,25)
train_accuracy = []
test_accuracy = []

for i, k in enumerate(k_values):
    # k from 1 to 25(exclude)
    knn = KNeighborsClassifier(n_neighbors=k)
    # Fit with knn
    knn.fit(x_train,y_train)
    #train accuracy
    train_accuracy.append(knn.score(x_train, y_train))
    # test accuracy
    test_accuracy.append(knn.score(x_test, y_test))
# Plot
plt.figure(figsize=[13,8])
plt.plot(k_values, test_accuracy, label = 'Testing Accuracy')
plt.plot(k_values, train_accuracy, label = 'Training Accuracy')
plt.legend()
plt.title('-value VS Accuracy')
plt.xlabel('Number of Neighbors')
plt.ylabel('Accuracy')
plt.xticks(k_values)
plt.savefig('graph.png')
plt.show()
print("Best accuracy is {} with K = {}".format(np.max(test_accuracy),1+test_accuracy.index(np.max(test_accuracy))))
```




```
Best accuracy is 0.734375 with K = 1
```

In [ ]: