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Matic no: **M.eng/SIPET/2022/13711**

Assignment

Prediction and analysis of hydraulic conductivity/Compressive strength of Lateritic soil - Bentonite mixtures using support vector machine

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importing the modules to be used

In [1]:
```
import pandas as pd
import numpy as np
from sklearn.svm import SVR
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, mean_squared_error
import matplotlib.pyplot as plt
import seaborn as sns
```

reading in the data

In [2]:
```
pd.read_excel("data/AI DATA ANALYSIS AND PREDICTION.xlsx")
ucs = pd.read_excel("data/UCS AI DATA.xlsx")
ucs.columns = ucs.loc[1]
ucs = ucs.drop([0,1], axis = 0).reset_index(drop = True)
ucs.head()
```

Out[2]:

1	Compactive Effort E	Moulding Water Content (%)	Bentonite content (%)	UCS (kN/m2)
0	RBSL	12.5	0	191.47
1	RBSL	15	0	184.55
2	RBSL	17.5	0	241.67
3	RBSL	20	0	138.34
4	RBSL	22.5	0	117.37

In [3]:
```
print(ucs.shape)
ucs.info()
```

```
(100, 4)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 4 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   Compactive Effort E         100 non-null    object
 1   Moulding Water Content (%)  100 non-null    object
 2   Bentonite content (%)       100 non-null    object
 3   UCS (kN/m2)                 100 non-null    object
dtypes: object(4)
memory usage: 3.3+ KB
```

In [4]:
```
ucs.columns
```

Out[4]:
```
Index(['Compactive Effort E', 'Moulding Water Content (%)',
       'Bentonite content (%)', 'UCS (kN/m2)'],
```

```
      dtype='object', name=1)
```

In [5]:
```
ucs['Moulding Water Content (%)'] = ucs['Moulding Water Content (%)'].astype(float)
ucs['Bentonite content (%)'] = ucs['Bentonite content (%)'].astype(float)
ucs['UCS (kN/m2)'] = ucs['UCS (kN/m2)'].astype(float)
```

In [6]:
```
ucs.isnull().sum()
```

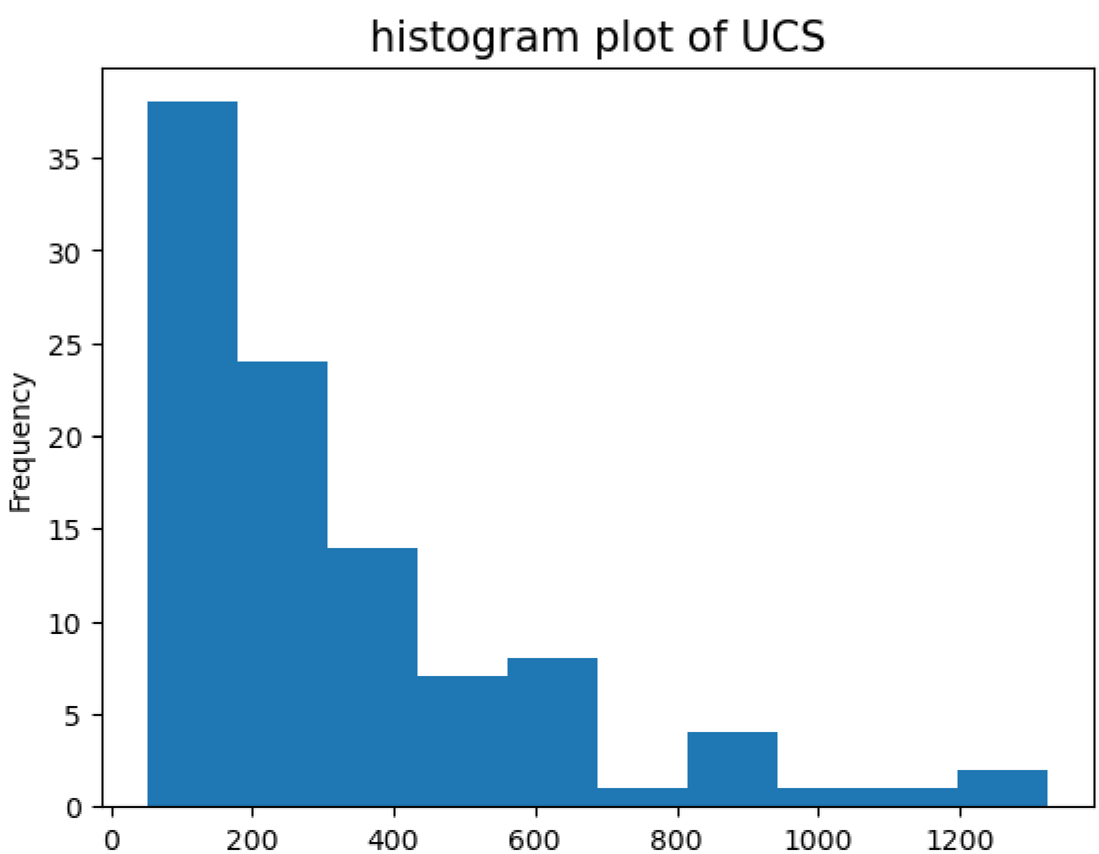
Out[6]:
```
1
Compactive Effort E           0
Moulding Water Content (%)    0
Bentonite content (%)         0
UCS (kN/m2)                   0
dtype: int64
```

In [7]:
```
ucs['UCS (kN/m2)'].max()
```

Out[7]:
```
1325.99
```

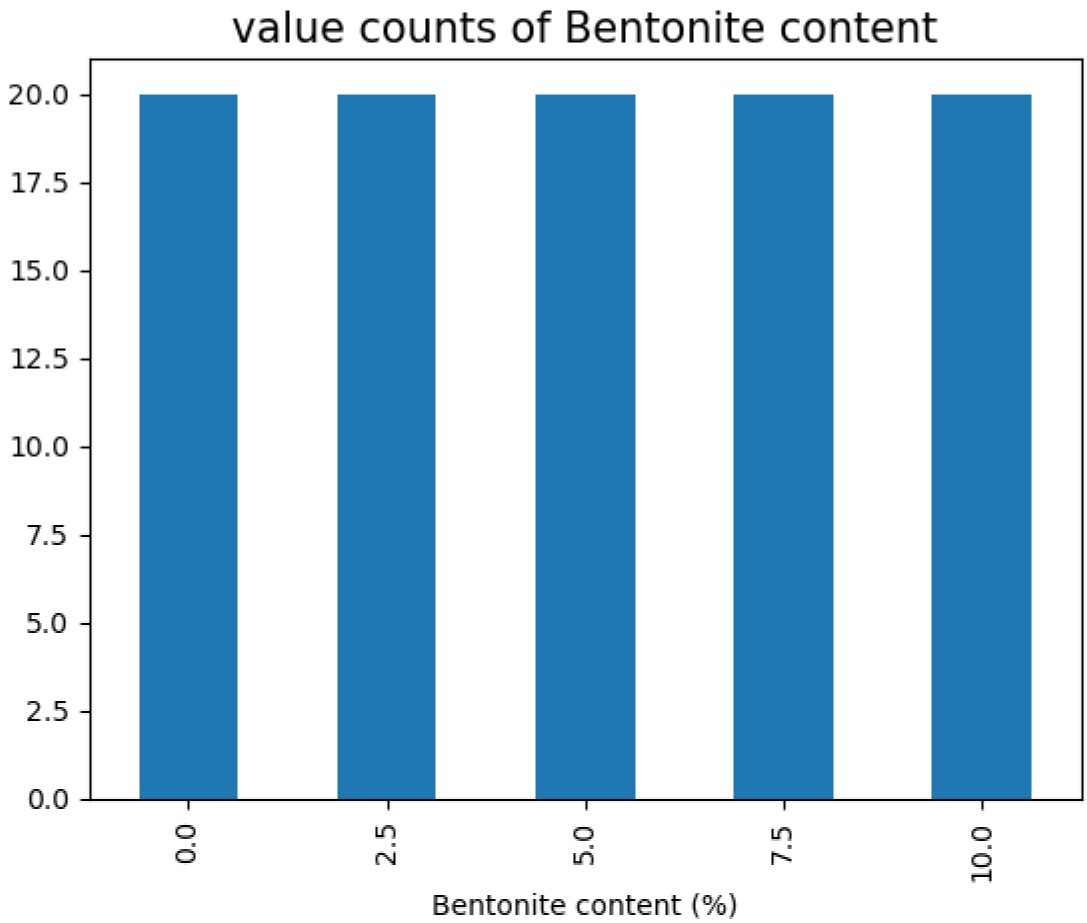
In [8]:
```
ucs['UCS (kN/m2)'].plot(kind = 'hist')
plt.title('histogram plot of UCS', fontsize = 15)
```

Out[8]:
```
Text(0.5, 1.0, 'histogram plot of UCS')
```



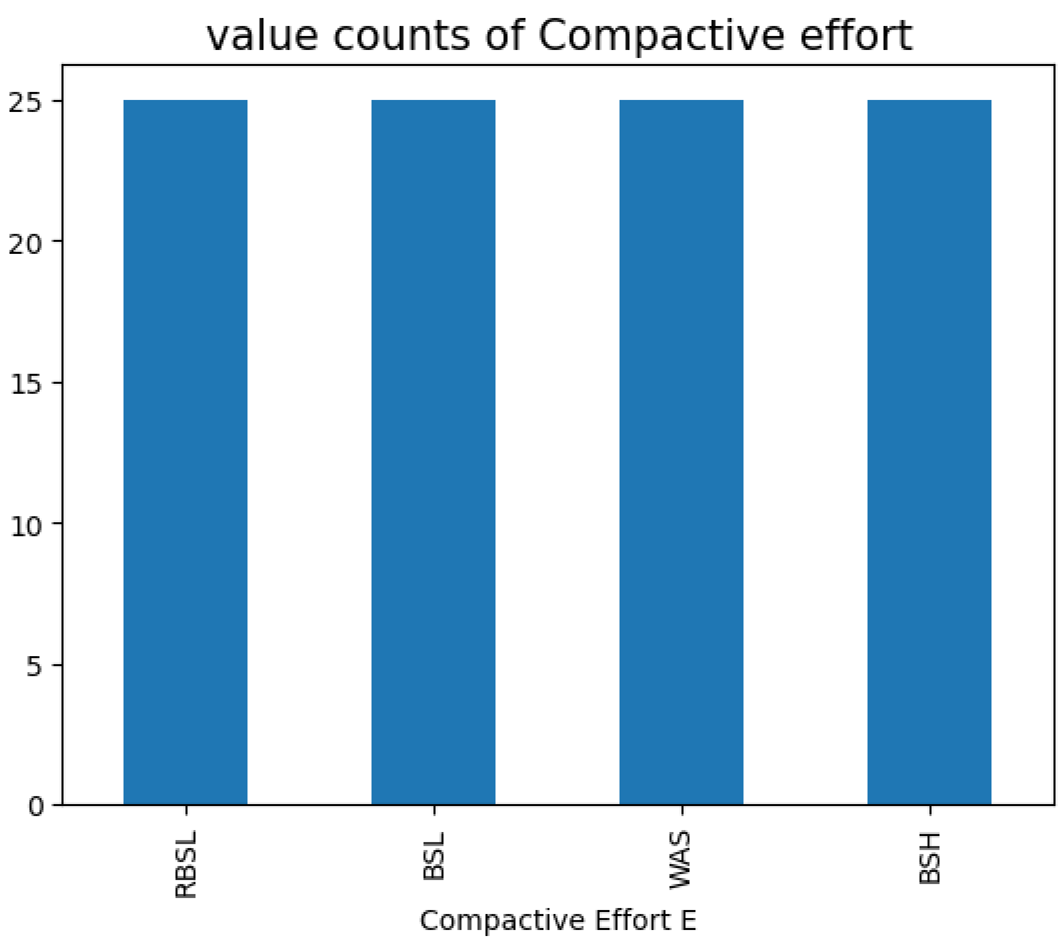
In [9]:
```
ucs['Bentonite content (%)'].value_counts().plot(kind = 'bar')
plt.title('value counts of Bentonite content', fontsize = 15)
```

Out[9]:
```
Text(0.5, 1.0, 'value counts of Bentonite content')
```



In [10]:
```
ucs['Compactive Effort E'].value_counts().plot(kind = 'bar')
plt.title('value counts of Compactive effort', fontsize = 15)
```

Out[10]:
```
Text(0.5, 1.0, 'value counts of Compactive effort')
```



Observations

- the target class is the Unconfined Compressive Strength (m/s)
- the target class is a float type number with most values between 0 and 200
- there are 100 data points with four columns
- there are no null value in the dataset
- the datatype for all the columns are object which need to be converted to numeric data type
- the comparative effort have four categories with 25 rows each
- Bentonite content have values containing quarters of 1 (i.e. 0.25, 0.5, 0.75, and 1.0)

In [11]:
```
sns.catplot(x = 'Moulding Water Content (%)', y = 'UCS (kN/m2)', hue = 'Compactive Effor
plt.xlabel('Moulding Water Content (%)')
plt.ylabel('UCS (kN/m2)')
plt.title('Moulding water content vs UCS(kN/m2) relationship', fontsize = 15)
plt.show()
```

```
C:\Users\USER\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_i
nf_as_na option is deprecated and will be removed in a future version. Convert inf value
s to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\USER\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_i
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```

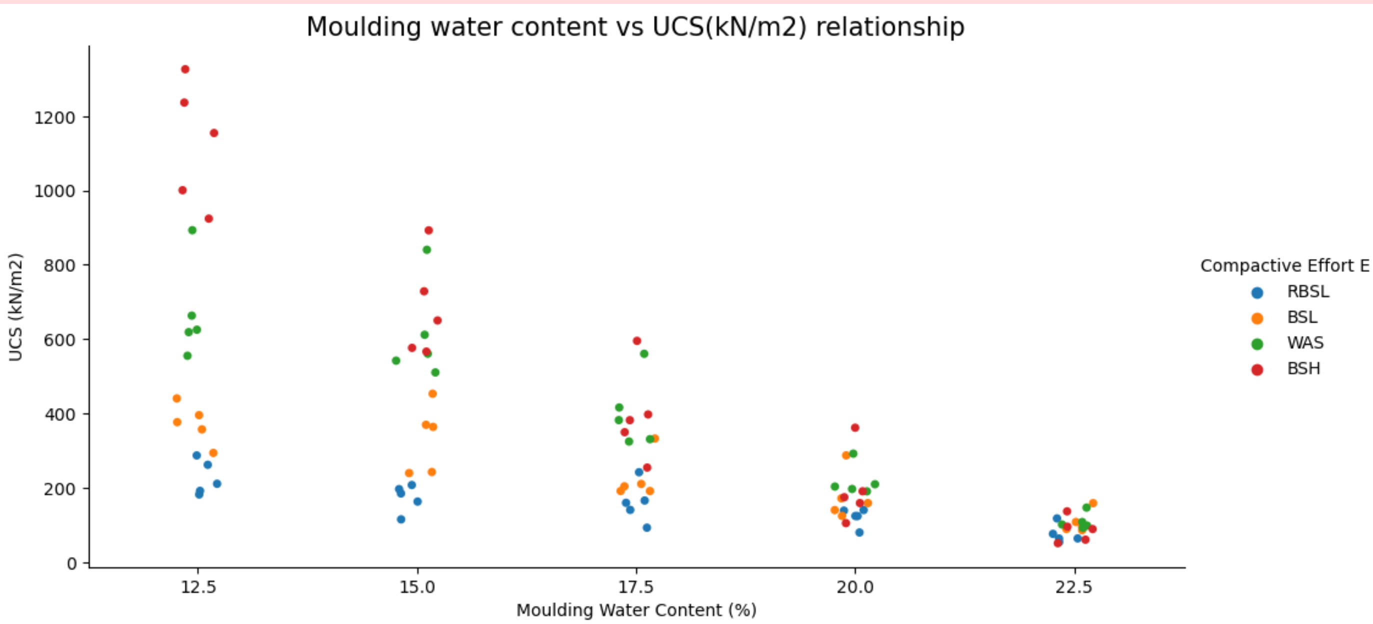

In [12]:
```
sns.catplot(x = 'Bentonite content (%)', y = 'UCS (kN/m2)', hue = 'Compactive Effort E',
plt.xlabel('Bentonite content (%)')
plt.ylabel('UCS (kN/m2)')
plt.title('Bentonite content (%) vs UCS(kN/m2) relationship', fontsize = 15)
plt.show()
```

```
C:\Users\USER\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_i
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```
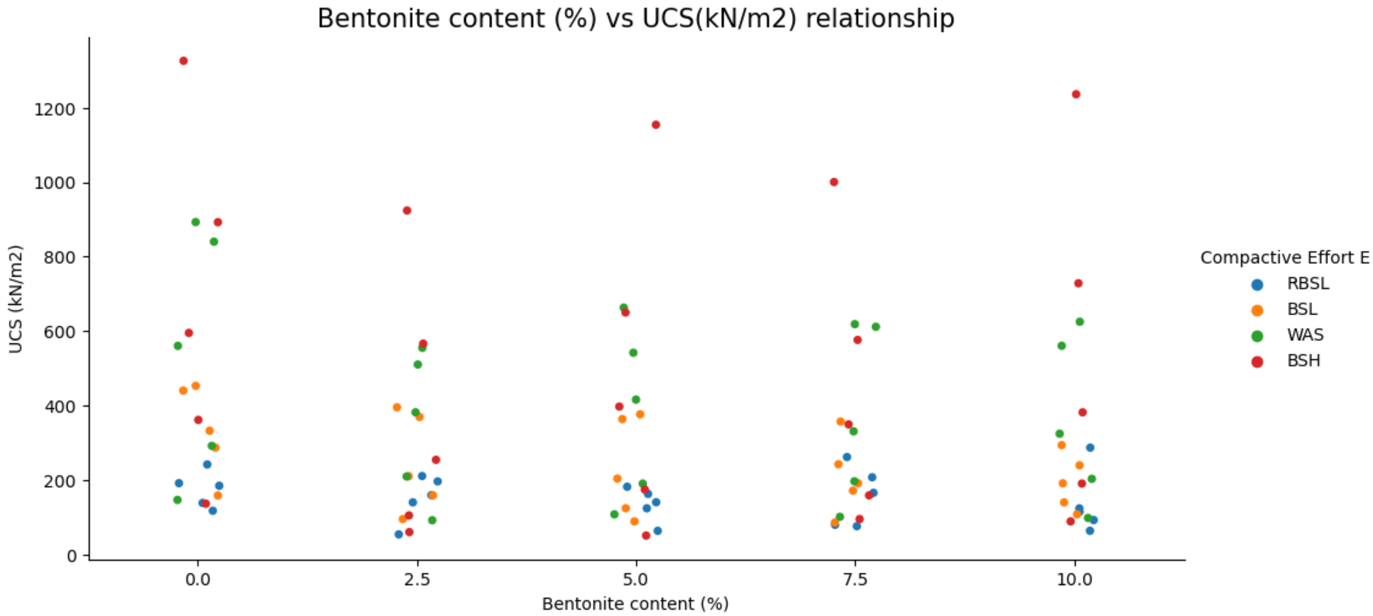
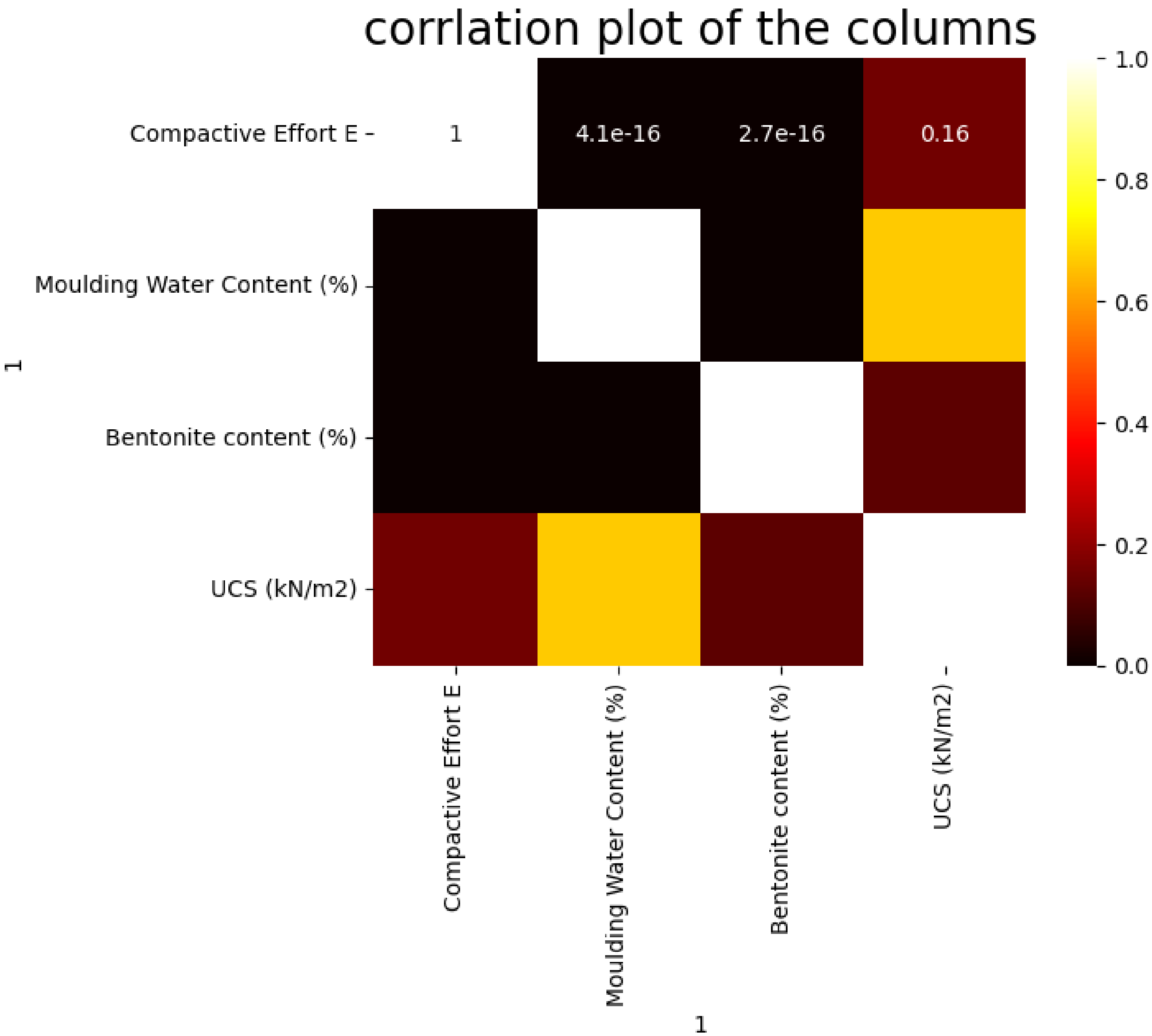



In [13]:
```
le = LabelEncoder()
ucs['Compactive Effort E'] = le.fit_transform(ucs['Compactive Effort E'])
for i, j in enumerate(le.classes_):
    print(f'{j} is encoded as {i}')
```

```
BSH is encoded as 0
BSL is encoded as 1
RBSL is encoded as 2
WAS is encoded as 3
```

In [14]:
```
sns.heatmap(ucs.corr().abs(), cmap = 'hot', annot = True)
plt.title('corrlation plot of the columns', fontsize = 20)
plt.show()
```



In [15]:
```
y = ucs.pop('UCS (kN/m2)')
X = ucs
```

In [16]:
```
display(X.head(2))
print(y[:5])
```

1	Compactive Effort E	Moulding Water Content (%)	Bentonite content (%)
0	2	12.5	0.0
1	2	15.0	0.0

```
0    191.47
1    184.55
2    241.67
3    138.34
4    117.37
Name: UCS (kN/m2), dtype: float64
```

splitting to 80% for training and 20% for testing while shuffling the data to ensure each class of compactive effort is distributed evenly

In [17]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, shuffle = Tru
```

support vector regressor

In [18]:
```
model = SVR()
```

In [19]:
```
model.fit(X_train, y_train)
```

Out[19]:
```
□ SVR
SVR()
```

In [20]:
```
prediction = model.predict(X_test)
```

In [21]:
```
np.sqrt(mean_squared_error(prediction, y_test))
```

Out[21]:
```
336.0494792510121
```

In [22]:
```
prediction
```

Out[22]:
```
array([201.543615  , 208.63071874, 203.70573768, 202.39393495,
       201.44947237, 196.92629469, 211.51355149, 195.20494493,
       203.63908243, 207.17188194, 195.95272776, 208.01933293,
       208.62080129, 211.7658616 , 199.33341996, 211.45584574,
       202.91808833, 198.49431038, 195.82845418, 211.51355365])
```

In [23]:
```
a = pd.DataFrame([prediction, y_test]).T
a.columns = ['prediction', 'actual value']
a['difference'] = a['actual value'] - a.prediction
a
```

Out[23]:

	prediction	actual value	difference
0	201.543615	287.01	85.466385
1	208.630719	369.31	160.679281
2	203.705738	140.31	-63.395738
3	202.393935	324.35	121.956065
4	201.449472	291.68	90.230528
5	196.926295	91.96	-104.966295
6	211.513551	1154.33	942.816449
7	195.204945	75.90	-119.304945
8	203.639082	415.91	212.270918
9	207.171882	611.51	404.338118
10	195.952728	50.71	-145.242728
11	208.019333	162.69	-45.329333
12	208.620801	840.17	631.549199
13	211.765862	924.01	712.244138
14	199.333420	190.26	-9.073420
15	211.455846	191.47	-19.985846
16	202.918088	330.58	127.661912
17	198.494310	136.41	-62.084310
18	195.828454	107.67	-88.158454
19	211.513554	555.06	343.546446

In [24]:

```
sns.catplot(x = 'prediction', y = "actual value", data = a, aspect =2)
plt.title('predicted values vs the actual values plot', fontsize = 20)
plt.xlabel('predicted values')
plt.ylabel('actual value')
plt.xticks(rotation = 45)
plt.show()
```

```
C:\Users\USER\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_i
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  with pd.option_context('mode.use_inf_as_na', True):
```

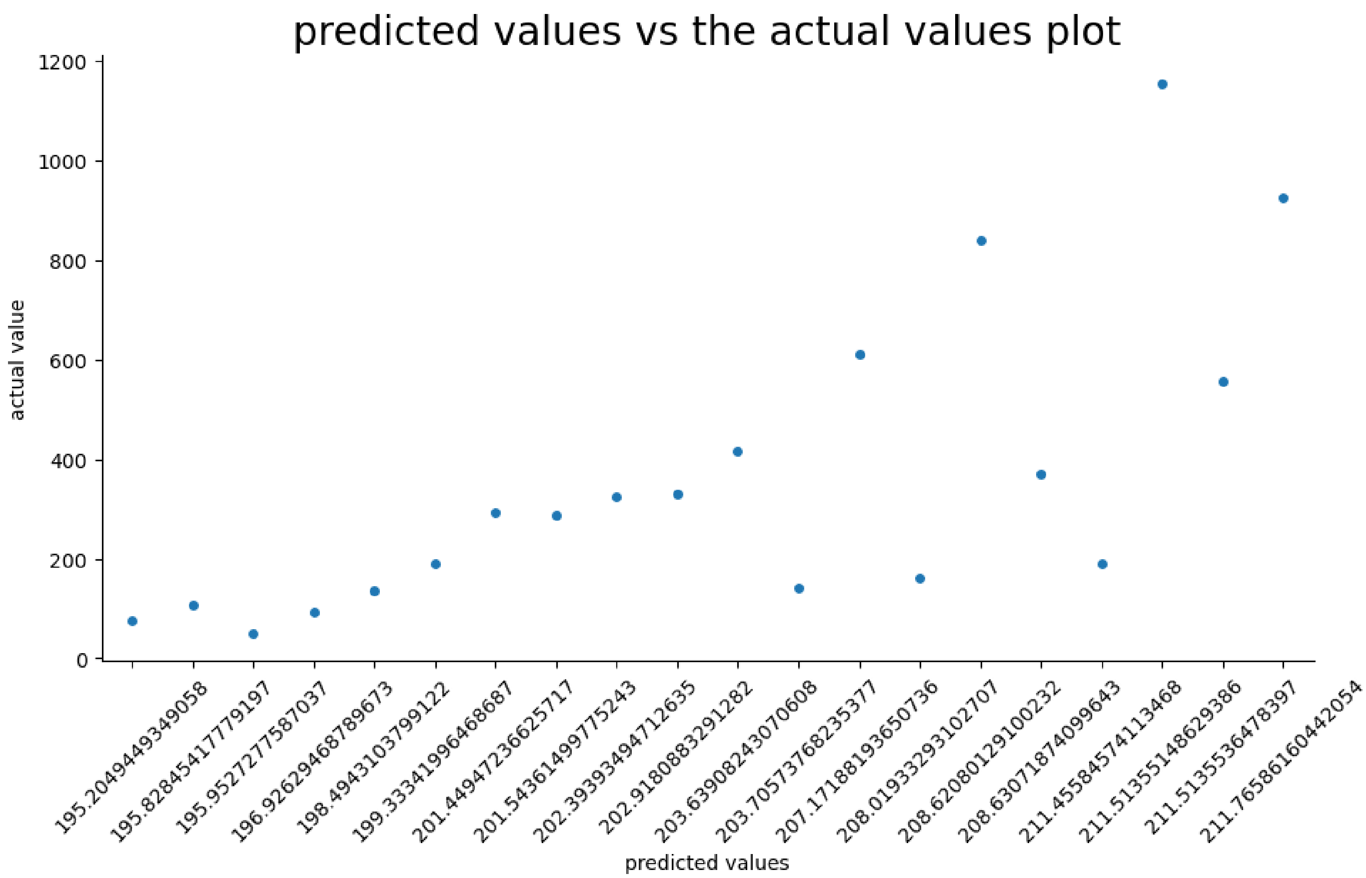

In [25]:

```
sns.catplot(x = 'prediction', y = "difference", data = a, aspect =2)
plt.xticks(rotation = 45)
plt.title('residual plot(predicted value vs difference between actual and predicted', fo
plt.show()
```

```
C:\Users\USER\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_i
nf_as_na option is deprecated and will be removed in a future version. Convert inf value
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  with pd.option_context('mode.use_inf_as_na', True):
```

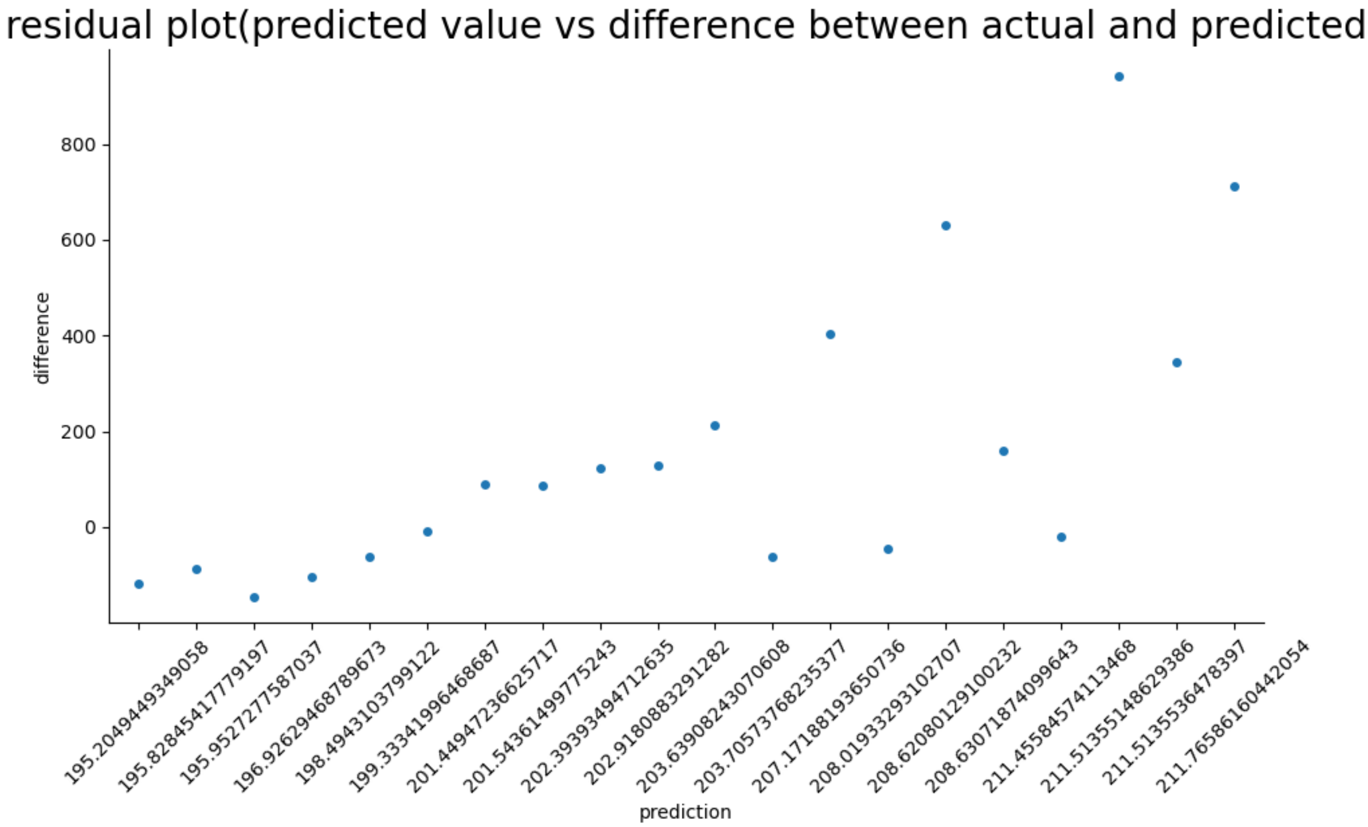

Conclusion

This study investigated the feasibility of using a Support Vector Machine (SVM) for predicting the Unconfined Compressive Strength (UCS) of Lateritic soil-Bentonite mixtures. The analysis revealed several key observations:

1. The target variable, UCS, is a continuous value ranging from 0 to 1400 (m/MPa), with most observations concentrated between 0 and 200 (m/MPa). This indicates a regression problem suitable for SVM application.
2. The dataset comprised 100 data points with four features, all initially in object format, requiring conversion to numerical data types for model training.
3. Interestingly, the "compactive effort" feature had four distinct categories with an equal number of data points in each, suggesting a potential influence on UCS.
4. Bentonite content exhibited a specific range with values representing quarters of 1 (0.25, 0.5, 0.75, and 1.0). This potentially allows for exploring the impact of varying Bentonite content on UCS.
5. While the model achieved a Root Mean Squared Error (RMSE) of 336, further optimization might be necessary to improve prediction accuracy, especially for values exceeding 200 (m/MPa).
6. The residual plot indicated a potential trend, suggesting a systematic error that could be addressed through model refinement or data transformation techniques.
7. The correlation coefficients between features and the target variable were generally low (around 20%). This suggests that non-linear relationships might exist between the features and UCS, potentially justifying the use of a non-linear model like SVM.y justifying the use of a non-linear model like SVM.
8. Moulding water content shows a high correlation with the hydraulic conductivity.

```
In [ ]:
```