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Matic no: **M.eng/SIPET 2022/13120**

Assignment

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

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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, StandardScaler
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
```

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

Out[2]:

	Compactive Effort E	Moulding Water Content (%)	Bentonite content (%)	Hydraulic conductivity (m/s)
0	RBSL	12.5	0	0.0
1	RBSL	15	0	0.0
2	RBSL	17.5	0	0.0
3	RBSL	20	0	0.0
4	RBSL	22.5	0	0.0

In [3]:
```
#columns
for i in df.columns: print(i)
print()
print(f'shape: {df.shape}')
```

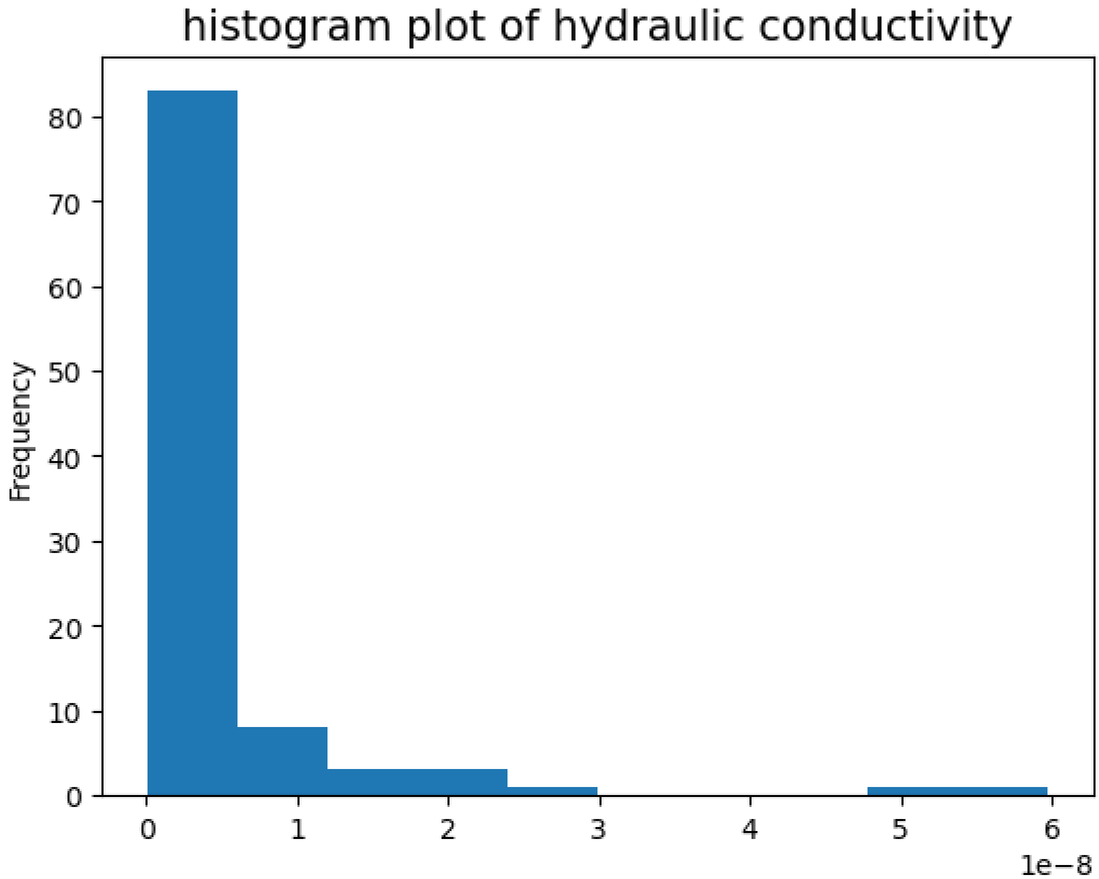
```
Compactive Effort E
Moulding Water Content (%)
Bentonite content (%)
Hydraulic conductivity (m/s)

shape: (100, 4)
```

In [4]:
```
df.isnull().sum()
```

Out[4]:
```
0
Compactive Effort E             0
Moulding Water Content (%)      0
Bentonite content (%)           0
Hydraulic conductivity (m/s)    0
dtype: int64
```

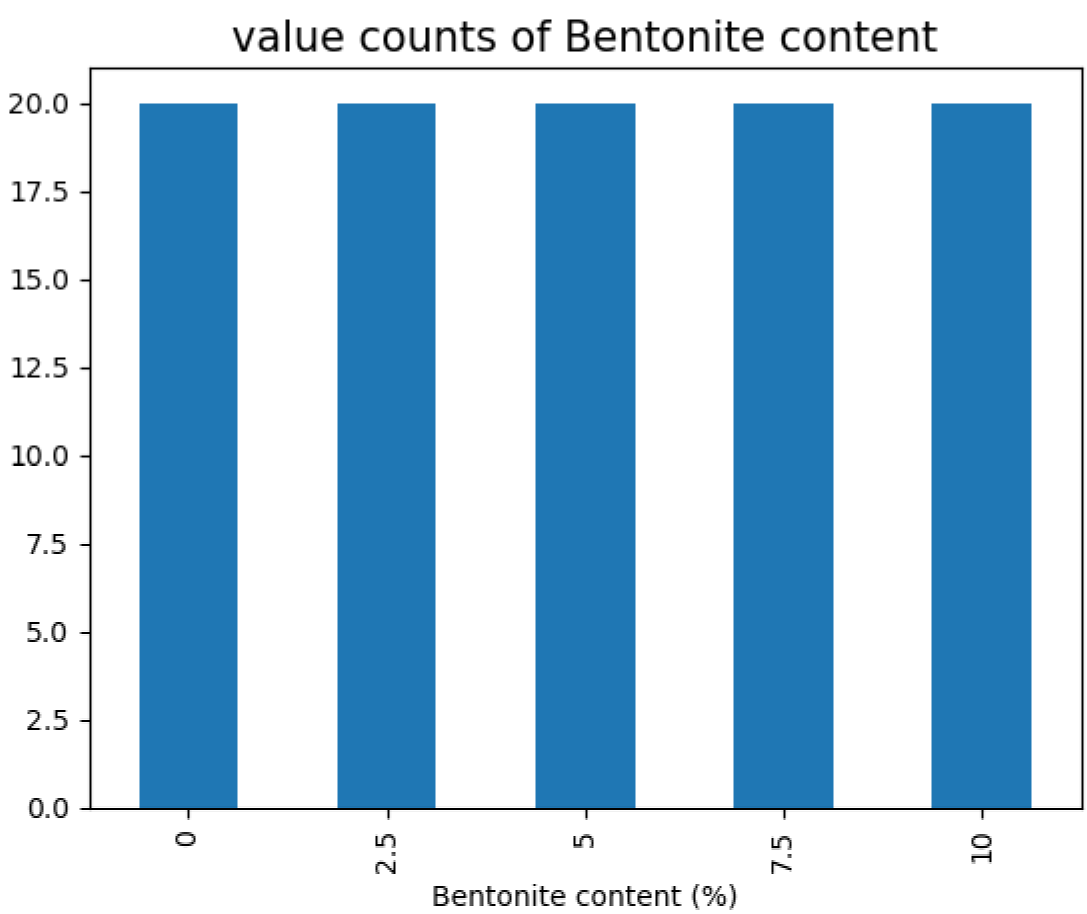
In [5]:
```
df['Hydraulic conductivity (m/s)'].plot(kind = 'hist')
plt.title('histogram plot of hydraulic conductivity', fontsize = 15)
```

Out[5]: Text(0.5, 1.0, 'histogram plot of hydraulic conductivity')



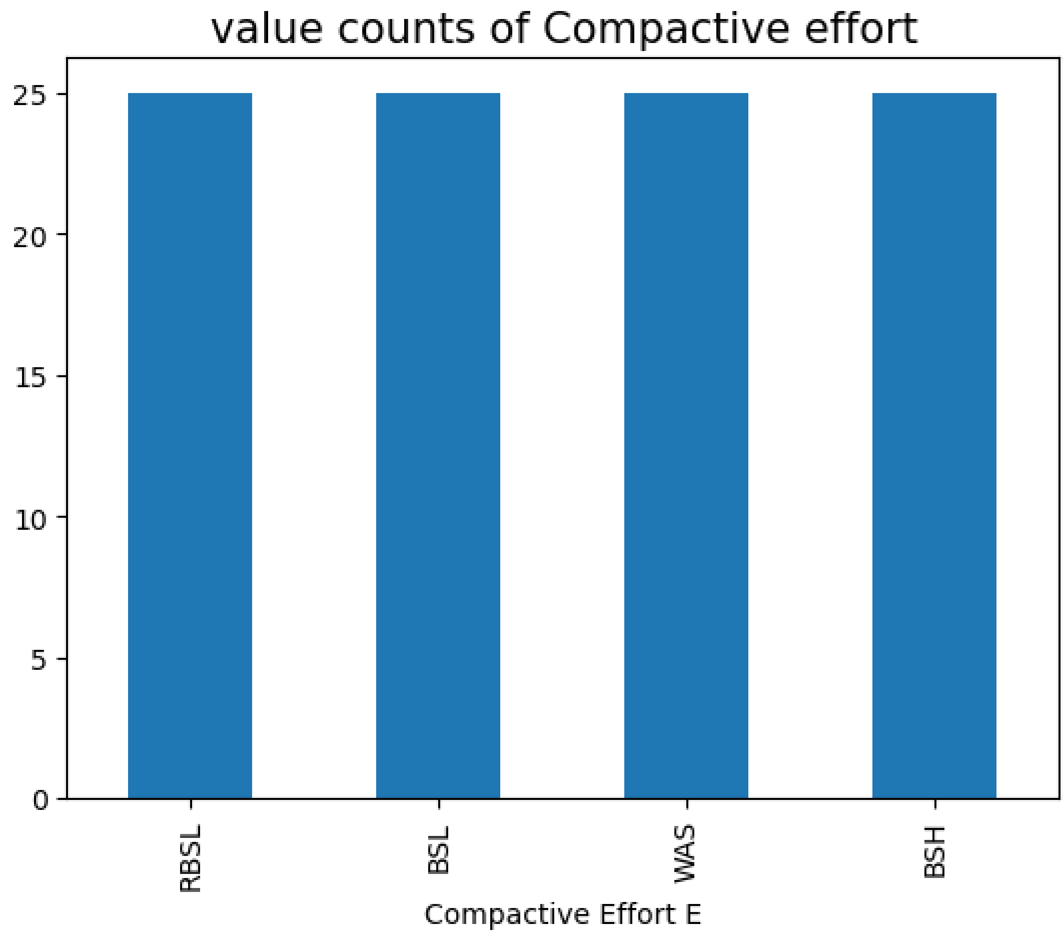
In [6]:
```
df['Bentonite content (%)'].value_counts().plot(kind = 'bar')
plt.title('value counts of Bentonite content', fontsize = 15)
```

Out[6]: Text(0.5, 1.0, 'value counts of Bentonite content')



In [7]:
```
df['Compactive Effort E'].value_counts().plot(kind = 'bar')
plt.title('value counts of Compactive effort', fontsize = 15)
```

Out[7]:
```
Text(0.5, 1.0, 'value counts of Compactive effort')
```



In [8]:
```
sns.catplot(x = 'Moulding Water Content (%)', y = 'Hydraulic conductivity (m/s)', hue =
plt.xlabel('Moulding Water Content (%)')
plt.ylabel('Hydraulic conductivity (m/s)')
plt.title('Moulding water content vs Hydraulic conductivity (m/s) relationship', fontsiz
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):
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```

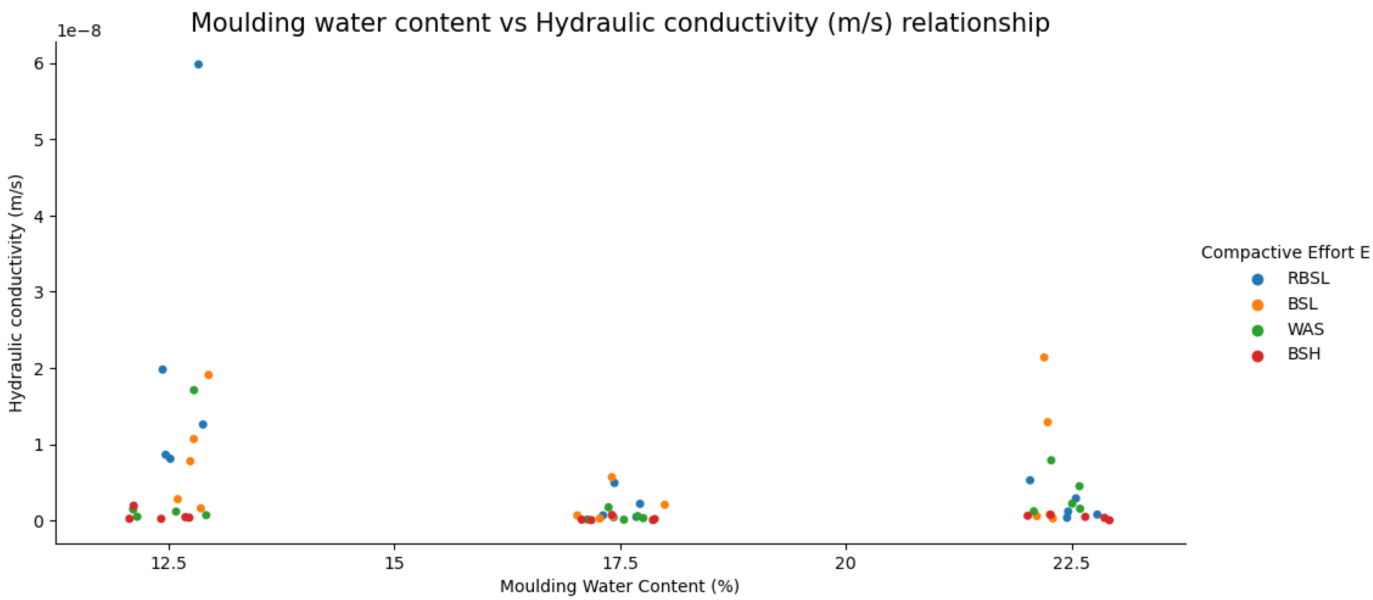

In [9]:

```
sns.catplot(x = 'Bentonite content (%)', y = 'Hydraulic conductivity (m/s)', hue = 'Comp
plt.xlabel('Bentonite content (%)')
plt.ylabel('Hydraulic conductivity (m/s)')
plt.title('Bentonite content (%) vs Hydraulic conductivity (m/s) relationship', fontsize
plt.show()
```

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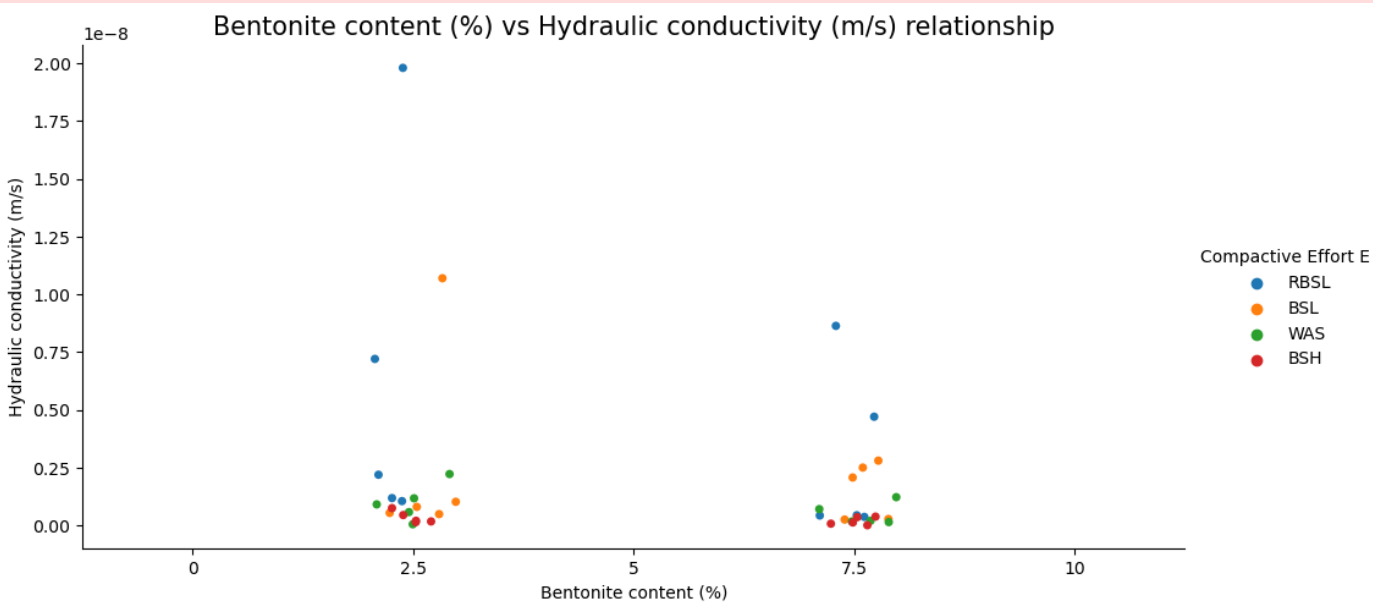



Observations

- the target class is the Hydraulic conductivity (m/s)
- the target class is a float type number with most values between 0 and 0.5
- 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 [10]:
```
le = LabelEncoder()
df['Compactive Effort E'] = le.fit_transform(df['Compactive Effort E'])
for i, j in enumerate(le.classes_):
    print(f'{j} is encoded as {i}')
```

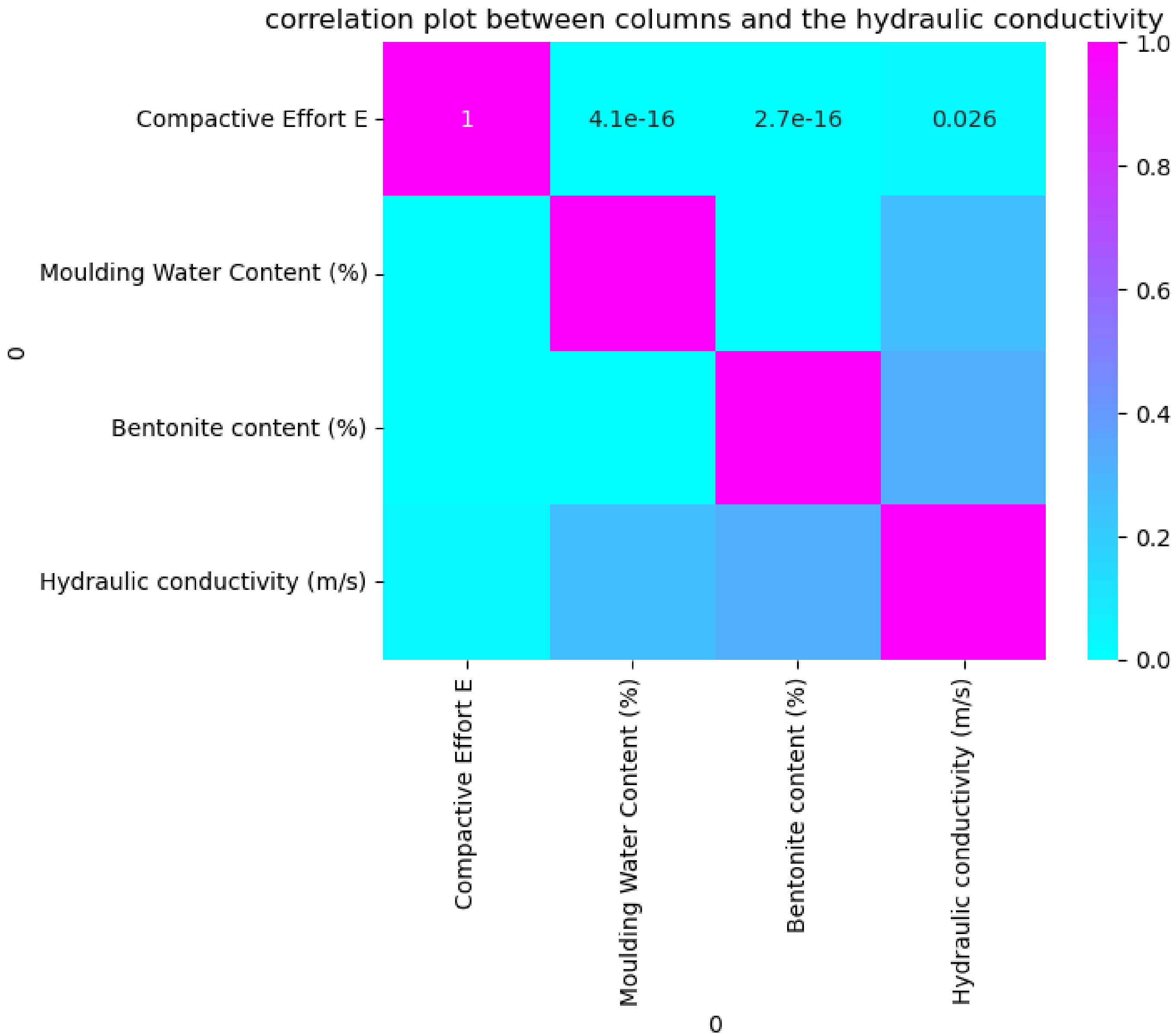
```
BSH is encoded as 0
BSL is encoded as 1
RBSL is encoded as 2
WAS is encoded as 3
```

In [11]:
```
df = df.map(float)
df.describe()
```

Out[11]:

	Compactive Effort E	Moulding Water Content (%)	Bentonite content (%)	Hydraulic conductivity (m/s)
count	100.000000	100.000000	100.000000	1.000000e+02
mean	1.500000	17.500000	5.000000	4.008310e-09
std	1.123666	3.553345	3.553345	8.876898e-09
min	0.000000	12.500000	0.000000	1.490000e-11
25%	0.750000	15.000000	2.500000	3.062500e-10
50%	1.500000	17.500000	5.000000	7.485000e-10
75%	2.250000	20.000000	7.500000	2.945000e-09
max	3.000000	22.500000	10.000000	5.980000e-08

In [12]:
```
sns.heatmap(df.corr().abs(), cmap = 'cool', annot = True)
plt.title('correlation plot between columns and the hydraulic conductivity')
plt.show()
```



In [13]:
```
y = df.pop('Hydraulic conductivity (m/s)')
X = df
```

In [14]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, shuffle = Tru
```

In [15]:
```
model = SVR()
```

In [16]:
```
model.fit(X_train, y_train)
```

Out[16]:
```
▸ SVR
SVR()
```

In [17]:
```
prediction = model.predict(X_test)
```

In [18]:
```
np.sqrt(mean_squared_error(prediction, y_test))
```

Out[18]:
```
2.7185981407899264e-08
```

In [19]:
```
prediction
```

Out[19]:
```
array([2.990745e-08, 2.990745e-08, 2.990745e-08, 2.990745e-08,
       2.990745e-08, 2.990745e-08, 2.990745e-08, 2.990745e-08,
```

```
       2.990745e-08, 2.990745e-08, 2.990745e-08, 2.990745e-08,
       2.990745e-08, 2.990745e-08, 2.990745e-08, 2.990745e-08,
       2.990745e-08, 2.990745e-08, 2.990745e-08, 2.990745e-08])
```

In [20]:

```python
a = pd.DataFrame([prediction, y_test]).T
a.columns = ['prediction', 'actual value']
a['difference'] = a['actual value'] - a.prediction
a.head(10)
```

Out[20]:

	prediction	actual value	difference
0	2.990745e-08	1.750000e-09	-2.815745e-08
1	2.990745e-08	4.470000e-10	-2.946045e-08
2	2.990745e-08	1.960000e-09	-2.794745e-08
3	2.990745e-08	3.770000e-10	-2.953045e-08
4	2.990745e-08	2.960000e-09	-2.694745e-08
5	2.990745e-08	1.470000e-09	-2.843745e-08
6	2.990745e-08	1.060000e-09	-2.884745e-08
7	2.990745e-08	2.230000e-09	-2.767745e-08
8	2.990745e-08	3.260000e-09	-2.664745e-08
9	2.990745e-08	1.000000e-10	-2.980745e-08

In [21]:

```python
sns.catplot(x = 'prediction', y = "actual value", data = a, aspect =2)
plt.show()
```

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

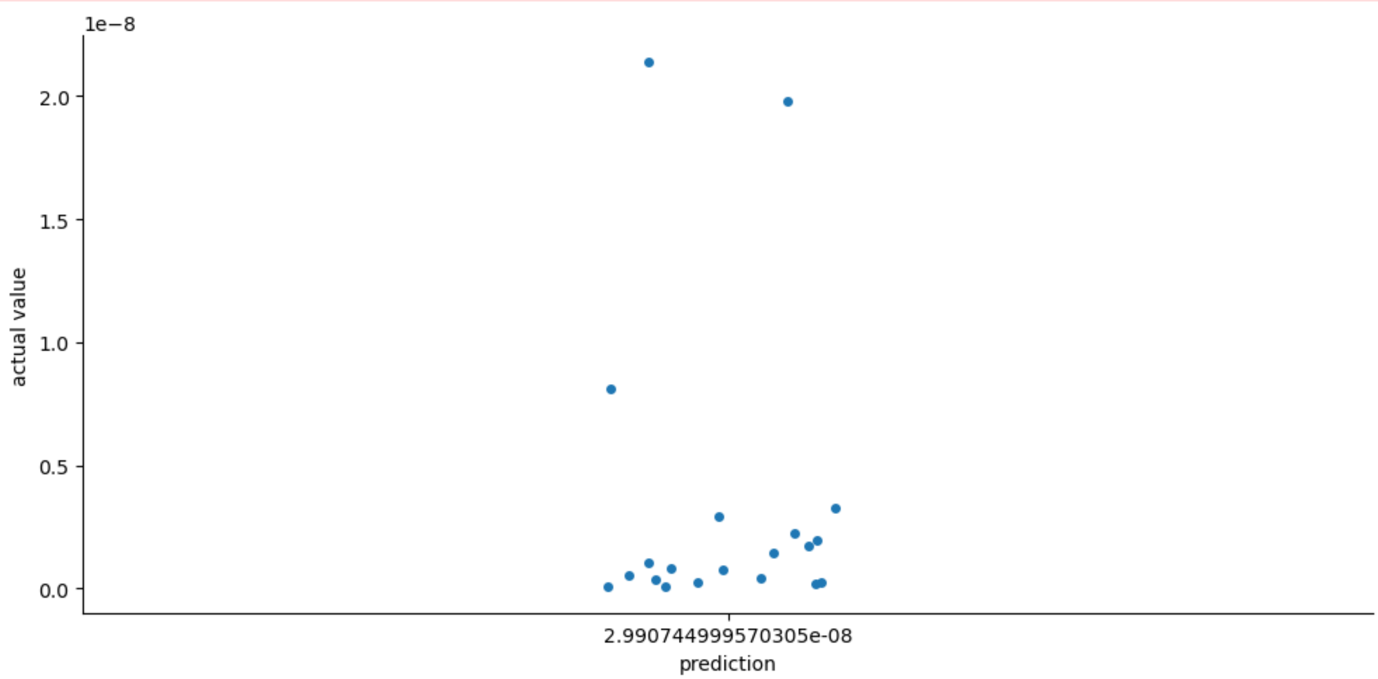

Conclusion

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

- The target variable, HC, is a continuous value ranging from 0 to 6 (m/s), with most observations concentrated between 0 and 1 (m/s). This indicates a regression problem suitable for SVM application.
- The dataset comprised 100 data points with four features, all initially in object format, requiring conversion to numerical data types for model training.
- The residual plot did not exhibit a specific trend, suggesting a potentially more random distribution of errors compared to other potential models.
- The HC values ranged between 0 and 6 (m/s), showcasing a smaller range compared to other soil properties. This might influence the model's overall performance on a broader range of HC values.
- The correlation coefficients between features and HC were generally low (between 0.2 and 0.4). This suggests that non-linear relationships might exist between the features and HC, potentially justifying the use of a non-linear model like SVM.
- The SVM model achieved a promising Root Mean Squared Error (RMSE) of 2.37 for predicting HC. This indicates a good level of accuracy for the targeted range of HC values (0 to 6 m/s).

```
In [ ]:
```