Wine Quality Prediction Model

Step 1: Importing and Analysing the data

- Importing the data and analysing the data.
- Preproccessing the data for null values

In [69]:
```
import pandas as pd
import numpy as np
```

In [70]:
```
data = pd.read_excel('Wine_Quality.xlsx')
```

In [71]:
```
data.head()
```

Out[71]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcoho
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4

In [72]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1599 entries, 0 to 1598
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   fixed acidity         1599 non-null   float64
 1   volatile acidity      1599 non-null   float64
 2   citric acid           1599 non-null   float64
 3   residual sugar        1599 non-null   float64
 4   chlorides             1599 non-null   float64
 5   free sulfur dioxide   1599 non-null   float64
 6   total sulfur dioxide  1598 non-null   float64
 7   density               1599 non-null   float64
 8   pH                    1598 non-null   float64
 9   sulphates             1599 non-null   float64
 10  alcohol               1599 non-null   float64
 11  quality               1598 non-null   float64
dtypes: float64(12)
memory usage: 150.0 KB
```

In [73]:
```
data[data['total sulfur dioxide'].isna()]
```

Out[73]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcoho
9	7.5	0.5	0.36	6.1	0.071	17.0	NaN	0.9978	3.35	0.8	10.!

In [74]:
```
data[data['pH'].isna()]
```

Out[74]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alco
184	6.7	0.62	0.21	1.9	0.079	8.0	62.0	0.997	NaN	0.58	

In [75]:
```
data[data['quality'].isna()]
```

Out[75]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alco
123	8.0	0.71	0.0	2.6	0.08	11.0	34.0	0.9976	3.44	0.53	

In [76]:
```
data.drop(9, axis = 0, inplace = True)
data.drop(184, axis = 0, inplace = True)
data.drop(123, axis = 0, inplace = True)
```

In [77]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1596 entries, 0 to 1598
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   fixed acidity         1596 non-null   float64
 1   volatile acidity      1596 non-null   float64
 2   citric acid           1596 non-null   float64
 3   residual sugar        1596 non-null   float64
 4   chlorides             1596 non-null   float64
 5   free sulfur dioxide   1596 non-null   float64
 6   total sulfur dioxide  1596 non-null   float64
 7   density               1596 non-null   float64
 8   pH                    1596 non-null   float64
 9   sulphates             1596 non-null   float64
 10  alcohol               1596 non-null   float64
 11  quality               1596 non-null   float64
dtypes: float64(12)
memory usage: 162.1 KB
```

Conclusion

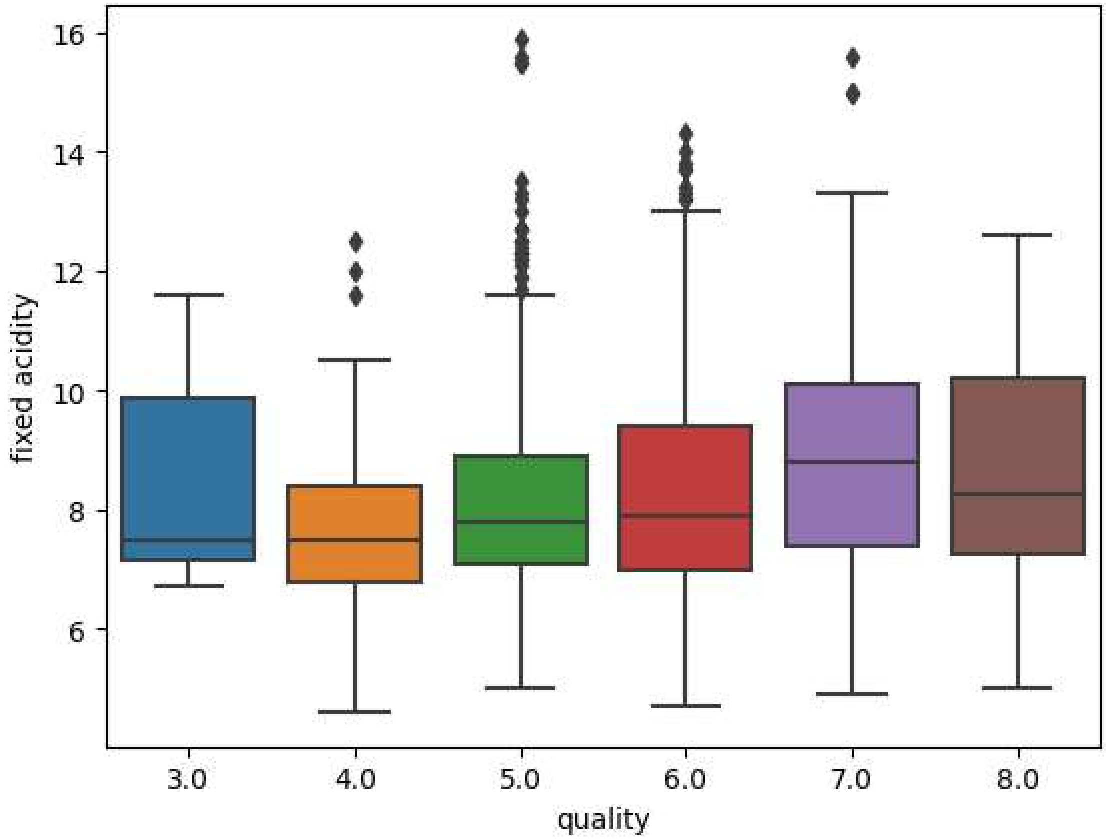
- We found three null values. the null values were removed from the dataset

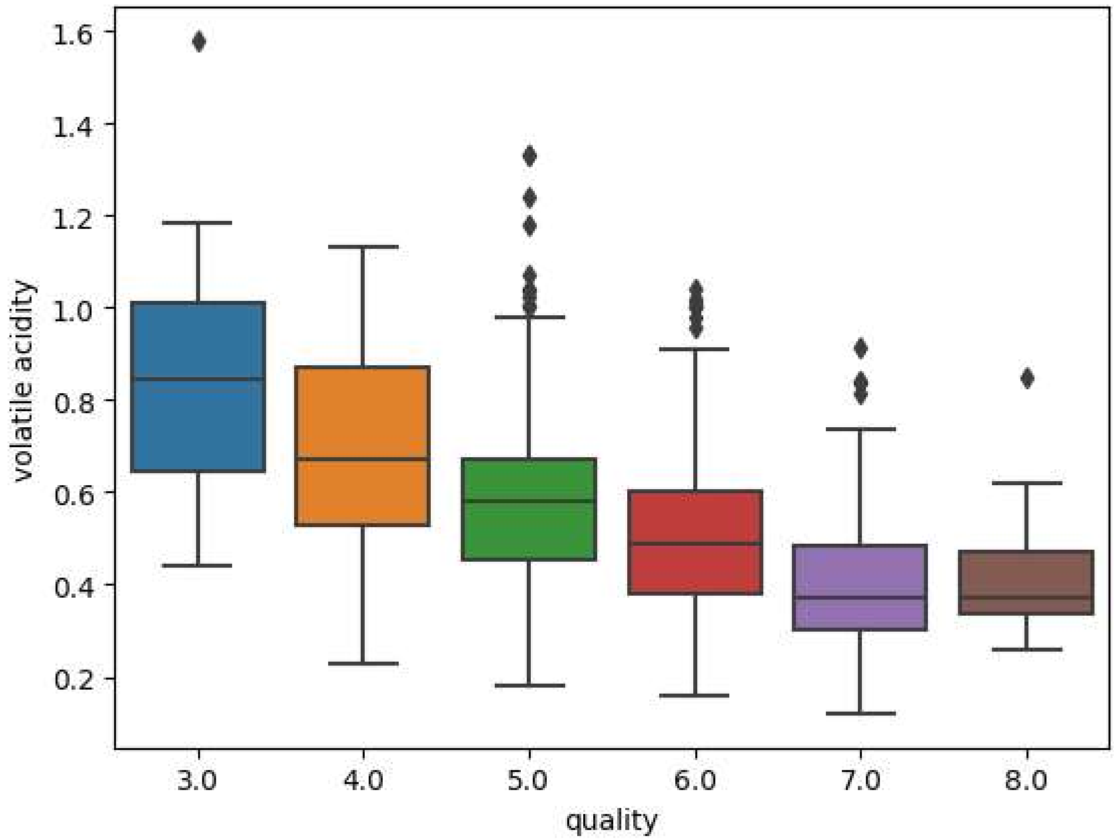
Step 2: Visualisng the data

- Visualising the data to understand which model to use.

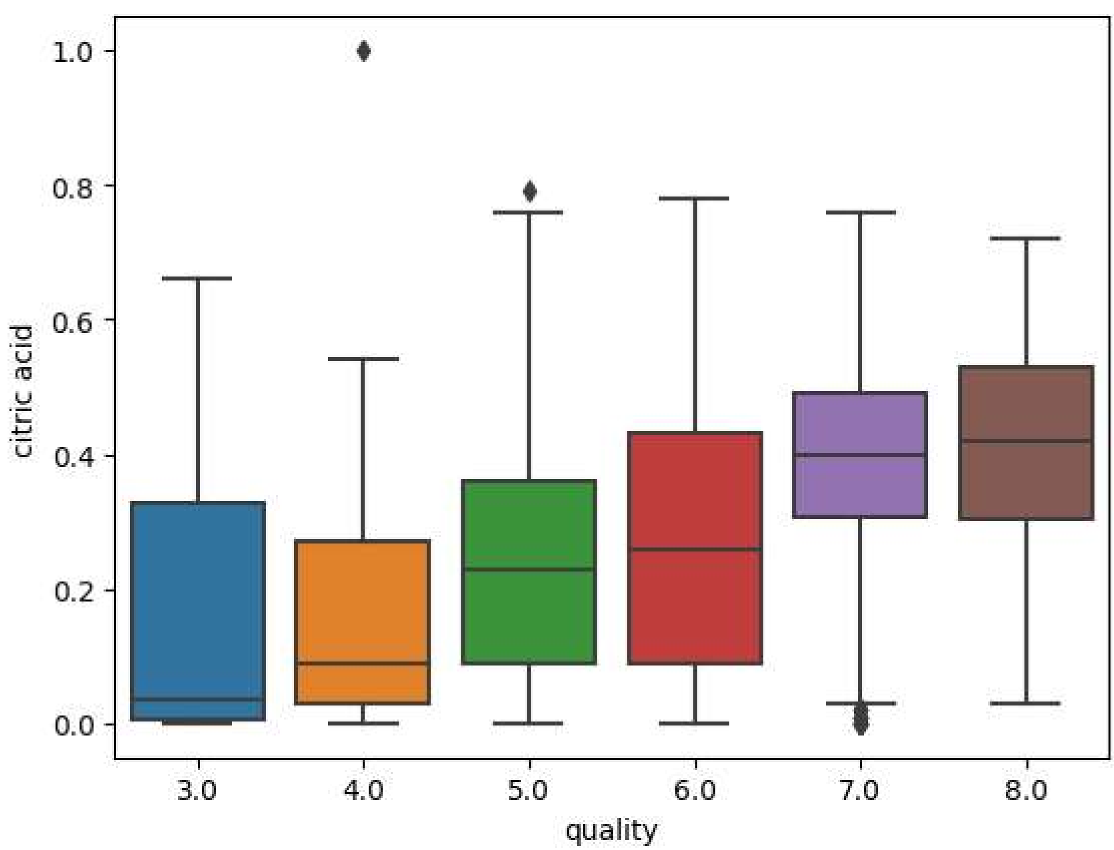
In [78]:

```
import seaborn as sns
import matplotlib.pyplot as plt
features = data.drop('quality', axis = 1).columns
for feature in features:
    sns.boxplot(x = 'quality',y = feature, data = data)
    plt.show()
```

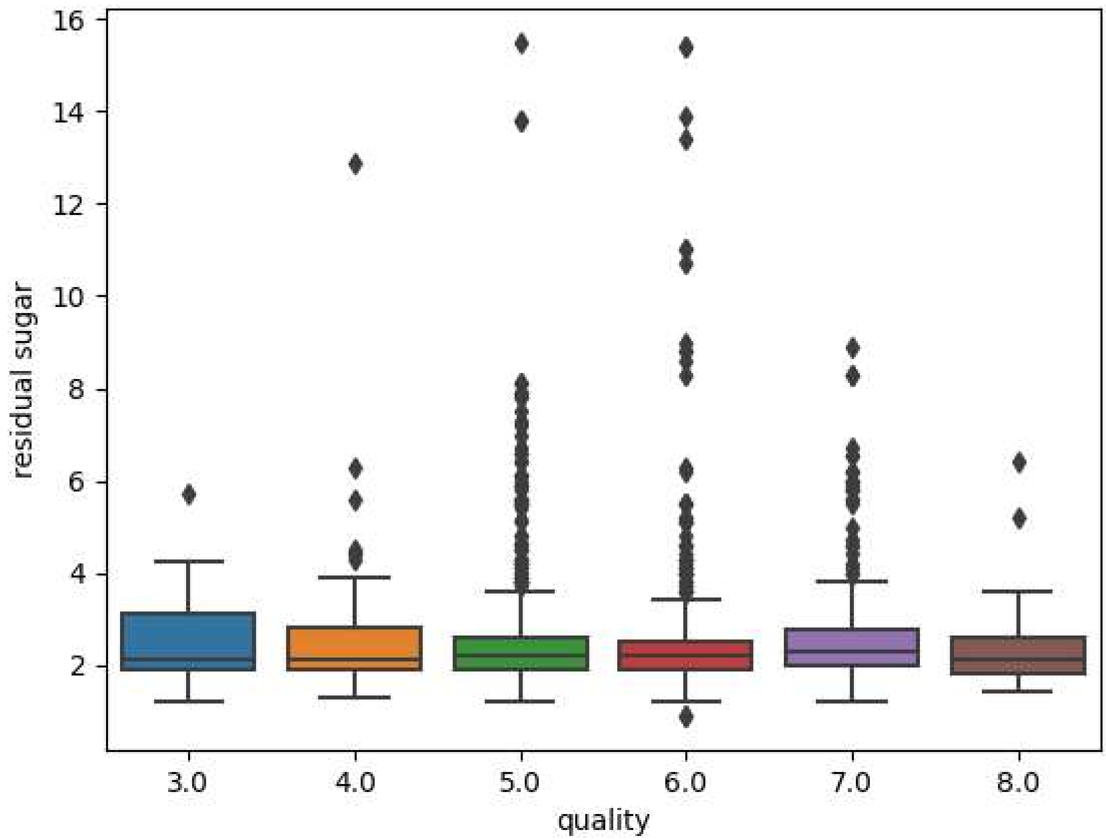


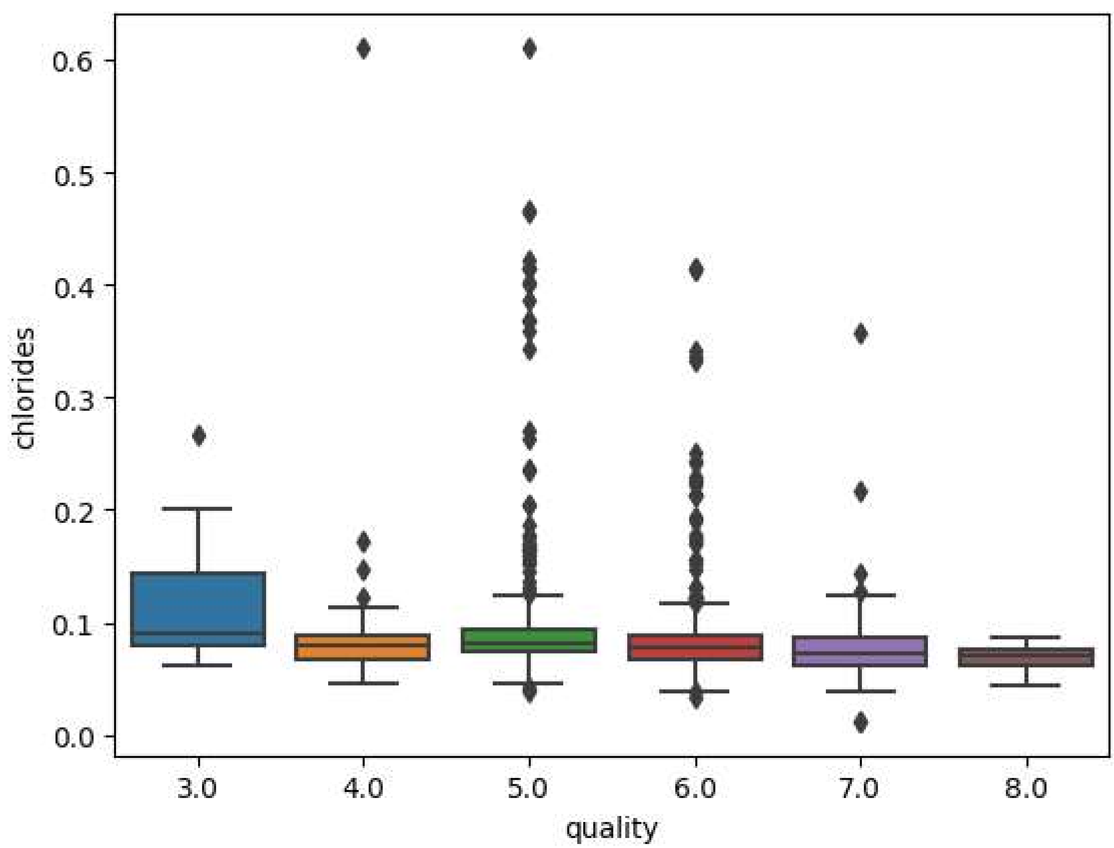


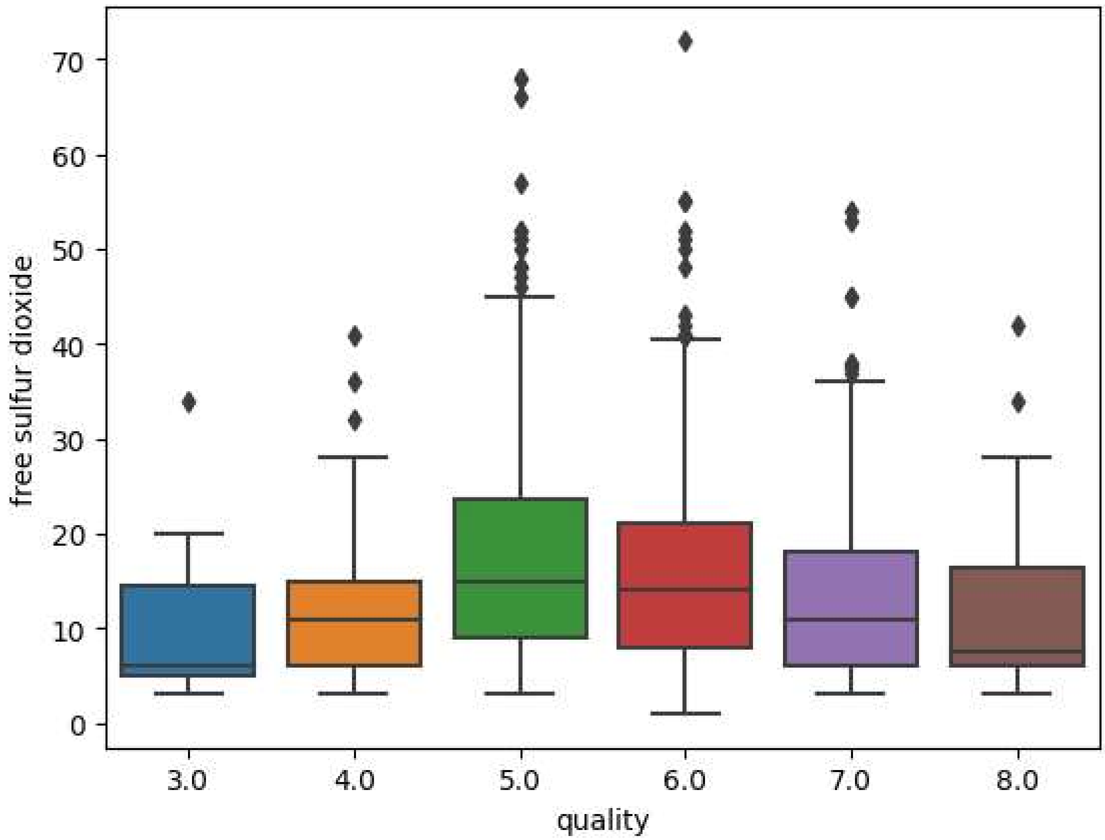
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
volatile acidity
3.0
4.0
5.0
6.0
7.0
8.0
quality

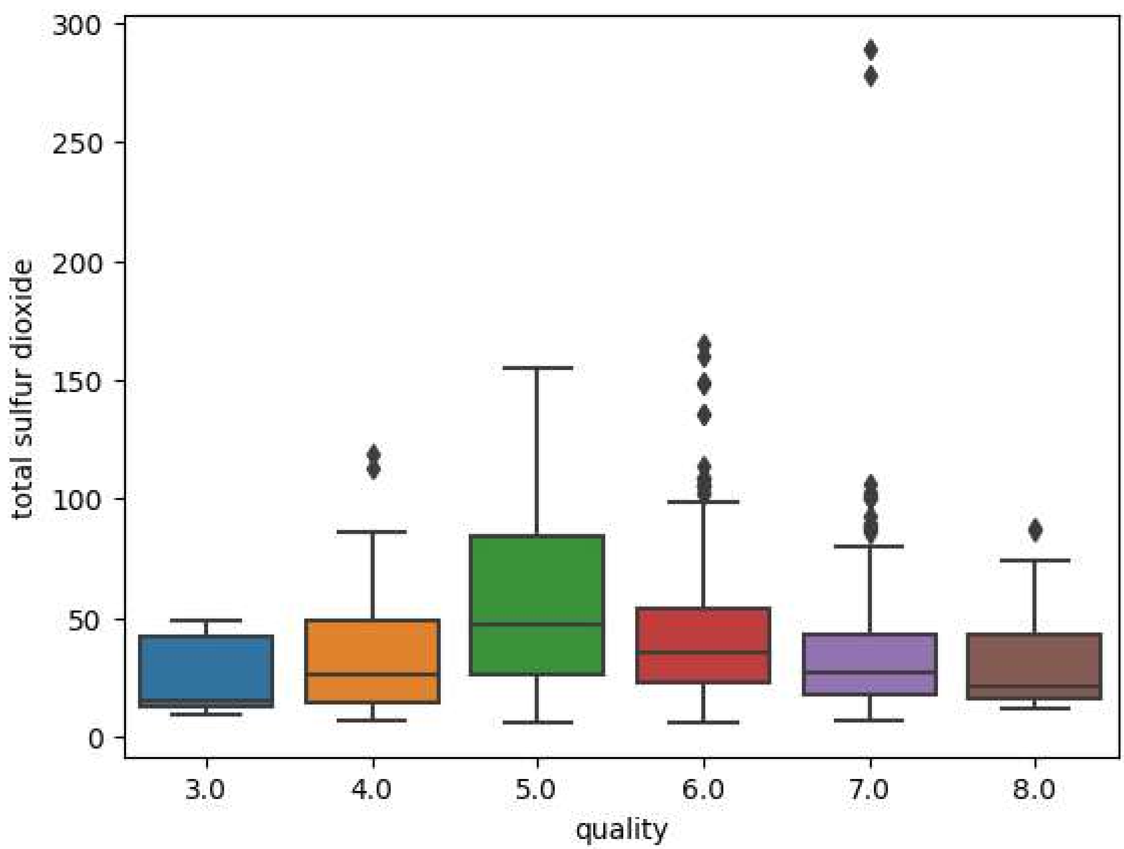


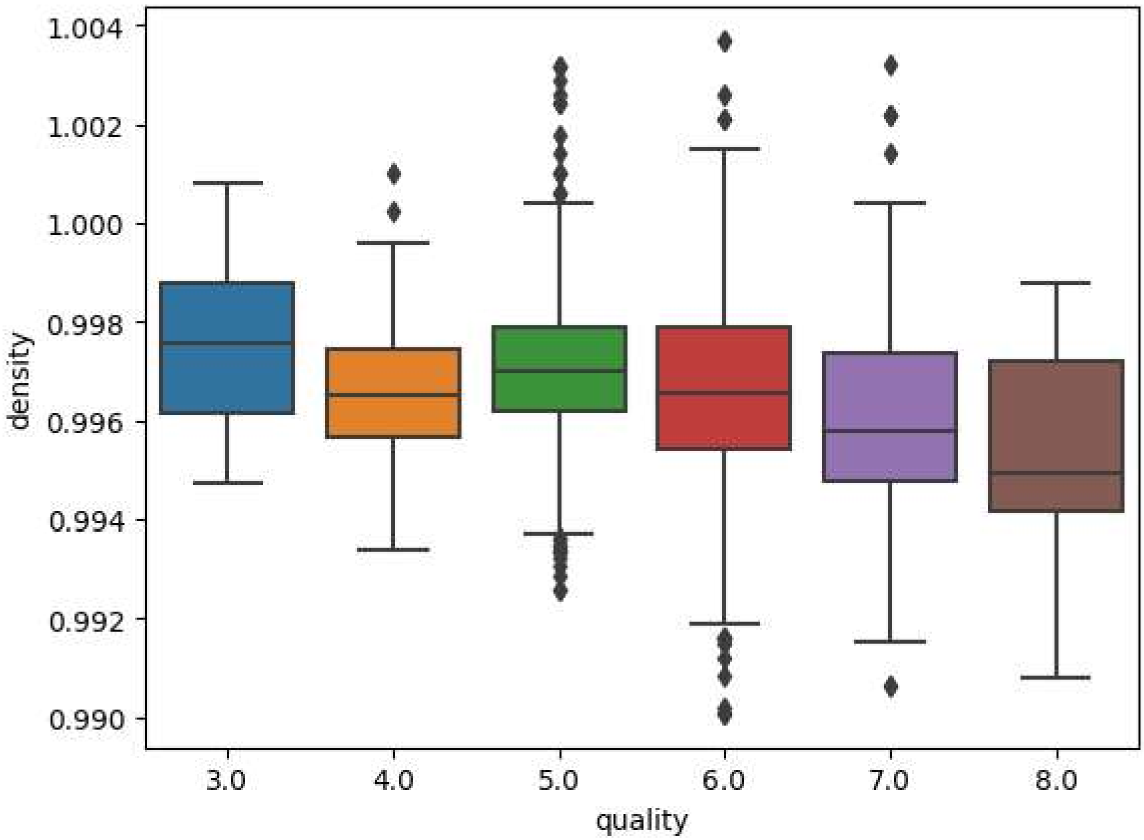
1.0
0.8
0.6
0.4
0.2
0.0
citric acid
3.0
4.0
5.0
6.0
7.0
8.0
quality

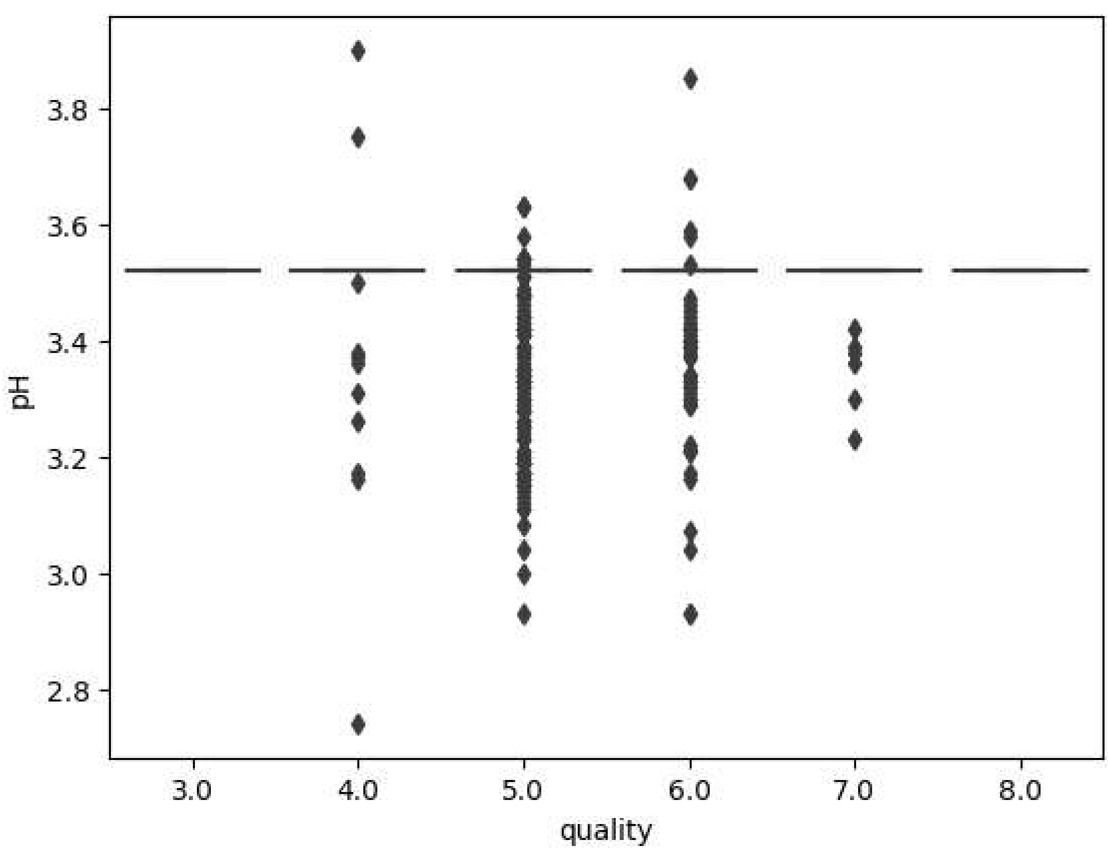

16
14
12
10
8
6
4
2
residual sugar
3.0
4.0
5.0
6.0
7.0
8.0
quality

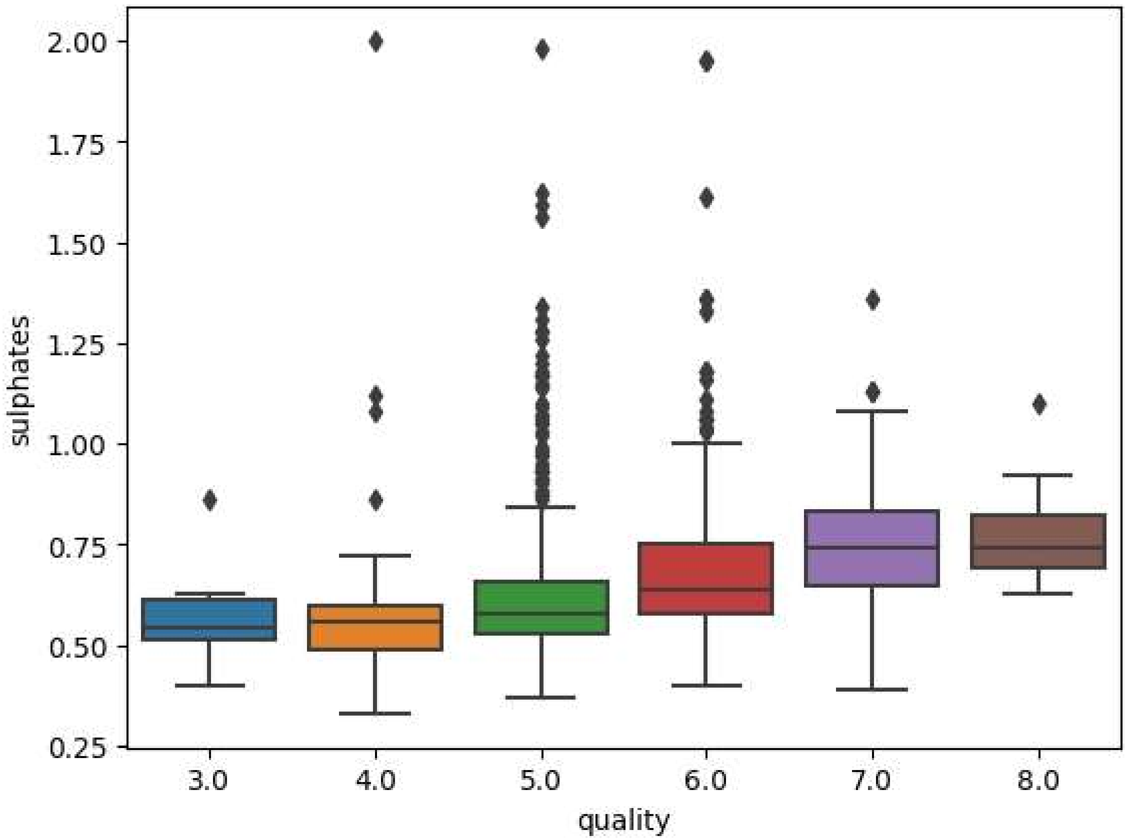

0.6
0.5
0.4
0.3
0.2
0.1
0.0
chlorides
3.0
4.0
5.0
6.0
7.0
8.0
quality

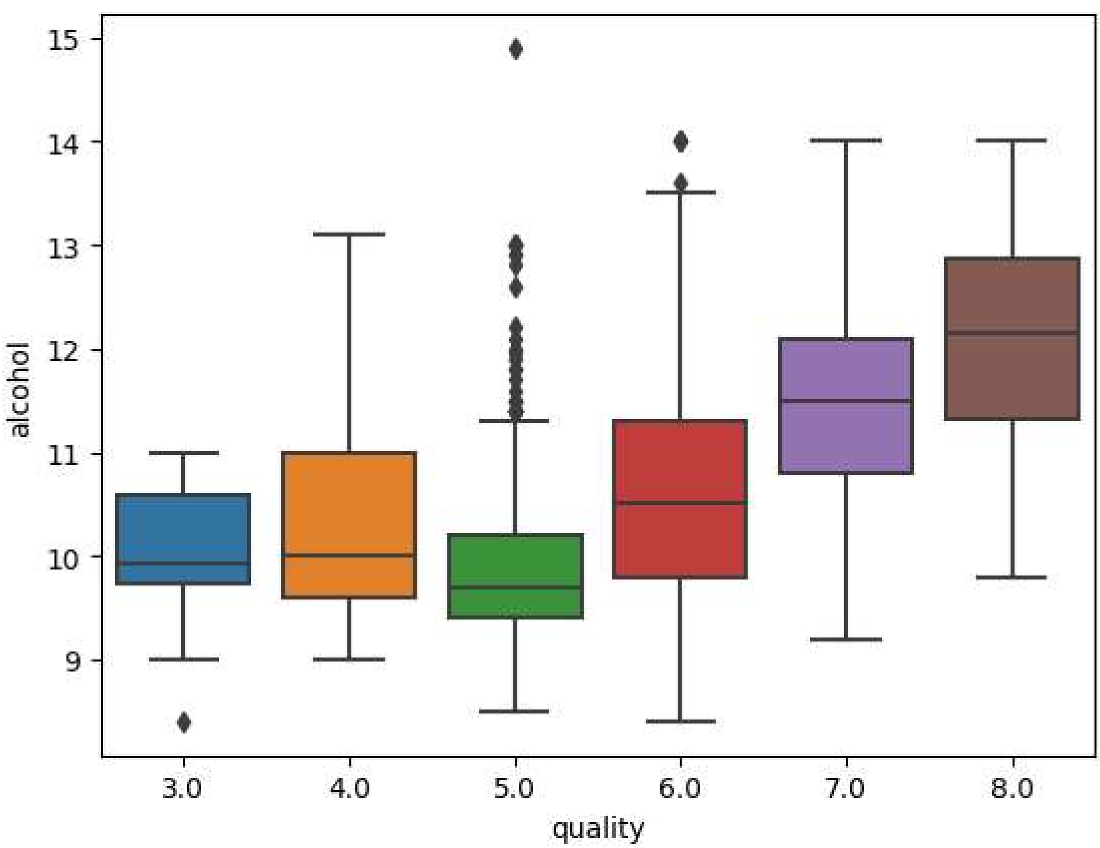

free sulfur dioxide
0
10
20
30
40
50
60
70
3.0
4.0
5.0
6.0
7.0
8.0
quality


total sulfur dioxide
0
50
100
150
200
250
300
3.0
4.0
5.0
6.0
7.0
8.0
quality


1.004
1.002
1.000
0.998
0.996
0.994
0.992
0.990
density
3.0
4.0
5.0
6.0
7.0
8.0
quality


3.8
3.6
3.4
3.2
3.0
2.8
pH
3.0
4.0
5.0
6.0
7.0
8.0
quality


2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
sulphates
3.0
4.0
5.0
6.0
7.0
8.0
quality


15
14
13
12
11
10
9
alcohol
3.0
4.0
5.0
6.0
7.0
8.0
quality

In [79]:
```
reviews = []
for i in data['quality']:
    if i >= 1 and i <= 3:
        reviews.append('1')
    if i >= 4 and i <= 7:
        reviews.append('2')
    if i >= 8 and i <= 10:
        reviews.append('3')
data['reviews'] = reviews
```

In [80]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1596 entries, 0 to 1598
Data columns (total 13 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   fixed acidity         1596 non-null   float64
 1   volatile acidity      1596 non-null   float64
 2   citric acid           1596 non-null   float64
 3   residual sugar        1596 non-null   float64
 4   chlorides             1596 non-null   float64
 5   free sulfur dioxide   1596 non-null   float64
 6   total sulfur dioxide  1596 non-null   float64
 7   density               1596 non-null   float64
 8   pH                    1596 non-null   float64
 9   sulphates             1596 non-null   float64
 10  alcohol               1596 non-null   float64
 11  quality               1596 non-null   float64
 12  reviews               1596 non-null   object 
dtypes: float64(12), object(1)
memory usage: 174.6+ KB
```

In [81]:
```
data['reviews'].value_counts()
```

Out[81]:
```
reviews
2    1568
3      18
1      10
Name: count, dtype: int64
```

Conclusion

- It is clear from the above visualisation, KNN can not be used.
- Regression model will be the most suitable for our scenario

Step 3: Constructing the model and checking accuracy

- There are many regression models. We will check the following models:

- Logistic Regression
- Decision Tree Classifier
- Random Forest Classifier

In [82]:
```
x = data.iloc[:, :11]
y = data['reviews']

x.head()
```

Out[82]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcoho
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4

In [83]:
```
y.head()
```

Out[83]:
```
0    2
1    2
2    2
3    2
4    2
Name: reviews, dtype: object
```

As the units of measurement is different, we need to use a scaler to scale the values, we use StandardScaler in this case

In [84]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
x = scaler.fit_transform(x)
```

In [85]:
```
x
```

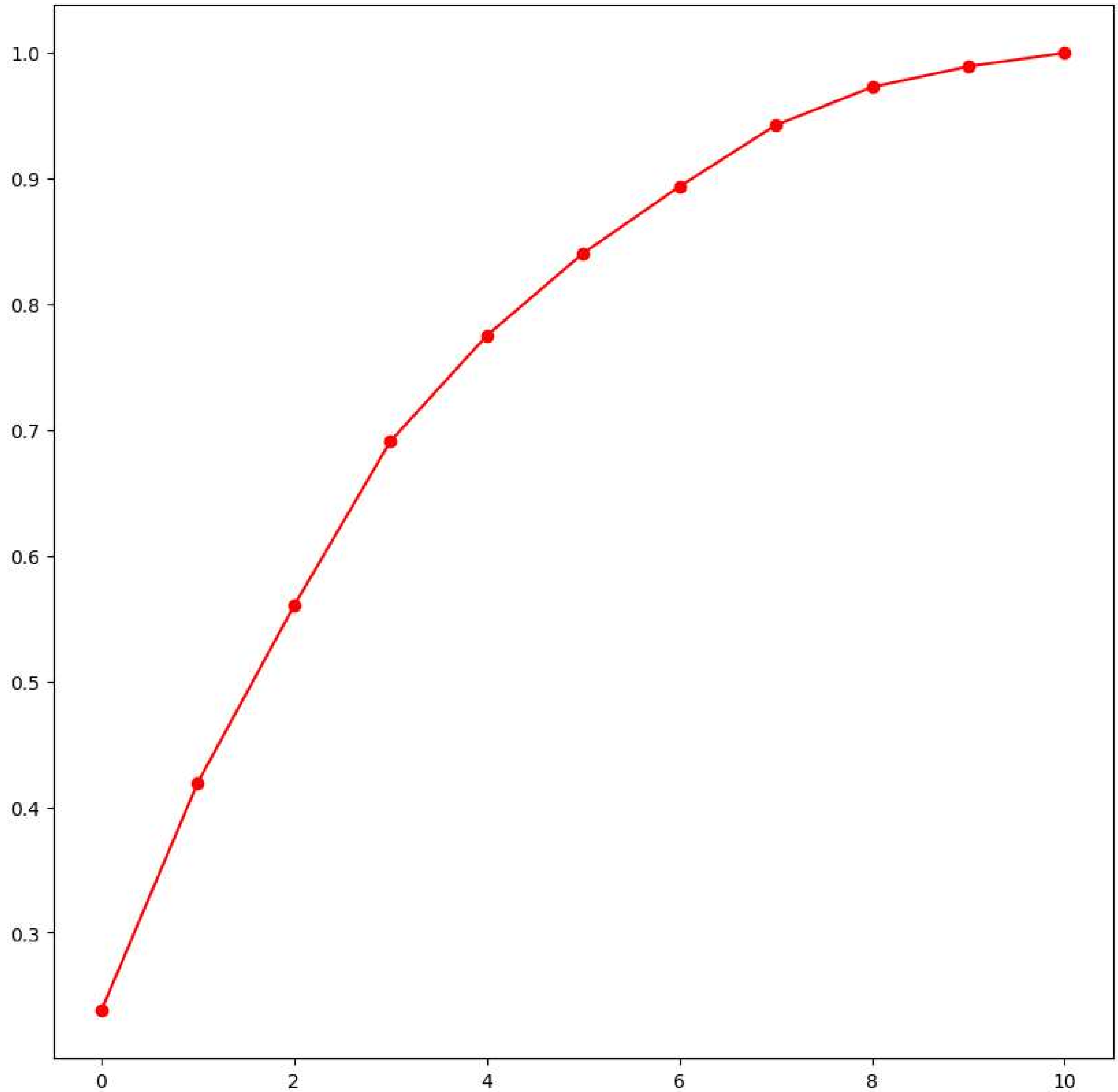
Out[85]:
```
array([[-0.52904176,  0.96223523, -1.39192434, ...,  0.14057855,
        -0.57917007, -0.9610637 ],
       [-0.2993646 ,  1.96727417, -1.39192434, ..., -3.72131159,
         0.12865108, -0.58572765],
       [-0.2993646 ,  1.29724821, -1.18657111, ..., -2.97384898,
        -0.04830421, -0.58572765],
       ...,
       [-1.16065393, -0.09863921, -0.72452634, ...,  0.26515565,
         0.54154675,  0.54028048],
       [-1.39033109,  0.65514   , -0.77586465, ...,  0.26515565,
         0.30560636, -0.21039161],
       [-1.3329118 , -1.21534915,  1.02097612, ...,  0.26515565,
         0.01068089,  0.54028048]])
```

PCA is used to reduce the dimensionality

In [86]:
```
from sklearn.decomposition import PCA
pca = PCA()

x_pca = pca.fit_transform(x)

plt.figure(figsize=(10, 10))
plt.plot(np.cumsum(pca.explained_variance_ratio_), 'ro-')
plt.show()
```



In [87]:
```
pca_new = PCA(n_components = 8)
x_new = pca_new.fit_transform(x)
```

In [88]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(x_new, y, test_size = 0.2(
```

In [89]:
```
X_train.shape
```

Out[89]:
```
(1276, 8)
```

In [90]:
```
X_test.shape
```

Out[90]:
```
(320, 8)
```

In [91]:
```
y_train.shape, y_test.shape
```

Out[91]:
```
((1276,), (320,))
```

Logistic Regression Model

In [92]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

lr = LogisticRegression()
lr.fit(X_train, y_train)
lr_predict = lr.predict(X_test)
```

In [93]:
```
accuracy_score(y_test, lr_predict)
```

Out[93]:
```
0.98125
```

- Logistic Regression Model can predict to 99.375% accuracy

Decision Tree Model

In [94]:
```
from sklearn.tree import DecisionTreeClassifier

dt = DecisionTreeClassifier()
dt.fit(X_train, y_train)
dt_predict = dt.predict(X_test)
```

In [95]:
```
accuracy_score(y_test, dt_predict)
```

Out[95]:
```
0.971875
```

- Decision Tree Model can predict to 97.18% accuracy

Random Forest Model

In [96]:
```
from sklearn.ensemble import RandomForestClassifier

rf = RandomForestClassifier()
rf.fit(X_train, y_train)
rf_predict = rf.predict(X_test)
```

In [97]:
```
accuracy_score(y_test, rf_predict)
```

Out[97]:
```
0.984375
```

- Random Forest Model can predict to 99.375% accuracy

Conclusion

- We tested our dataset on various regression models.
- The best accuracy could be achieved using Random Forest Model and Logistic Regression Model
- Random Forest Model is best suited