ML ASSIGNMENT 1 SET 3 QUESTION 1

WORK NEED TO DO AS FOLLOWING:

1. Import the dataset from https://newonlinecourses.science.psu.edu/stat501/sites/onlinecourses.science.psu.edu.stat501/files/data/leukemia_remission/index.txt (https://newonlinecourses.science.psu.edu/stat501/sites/onlinecourses.science.psu.edu.stat501/files/data/leukemia_remission/index.txt) (Links ##### to an external site.)(Hint: Convert txt to csv for ease of use.)

2. Extract X as all columns except the first column and Y as first column.

3. Visualize the dataset.

4. Split the data into training set and testing set. Perform 10-fold cross validation.

5. Train a Logistic regression model for the dataset.

6. Display the coefficients and form the logistic regression equation.

7. Compute the accuracy and confusion matrix.

8. Display the correlation between all the attributes.

Importing all required libraries

In [106]:

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import KFold
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import ConfusionMatrixDisplay
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
import os
```

1. Import the dataset from https://newonlinecourses.science.psu.edu/stat501/sites/onlinecourses.science.psu.edu.stat501/files/data/leukemia_remission/index.txt (https://newonlinecourses.science.psu.edu/stat501/sites/onlinecourses.science.psu.edu.stat501/files/data/leukemia_remission/index.txt) (Links ##### to an external site.)(Hint: Convert txt to csv for ease of use.)

In [107]:

```
# Reading data set from current directory
THIS_FOLDER=os.getcwd() #getting current working directory
print(THIS_FOLDER)
input_file = os.path.join(THIS_FOLDER, 'Cancer_det.csv')
data=pd.read_csv(input_file)
data.head(20)
```

```
C:\Users\kdevanand\ML
```

Out[107]:

	State	Lat	Mort	Ocean	Long
0	Alabama	33.0	219	1	87.0
1	Arizona	34.5	160	0	112.0
2	Arkansas	35.0	170	0	92.5
3	California	37.5	182	1	119.5
4	Colorado	39.0	149	0	105.5
5	Connecticut	41.8	159	1	72.8
6	Delaware	39.0	200	1	75.5
7	Wash D.C.	39.0	177	0	77.0
8	Florida	28.0	197	1	82.0
9	Georgia	33.0	214	1	83.5
10	Idaho	44.5	116	0	114.0
11	Illinois	40.0	124	0	89.5
12	Indiana	40.2	128	0	86.2
13	Iowa	42.2	128	0	93.8
14	Kansas	38.5	166	0	98.5
15	Kentucky	37.8	147	0	85.0
16	Louisiana	31.2	190	1	91.8
17	Maine	45.2	117	1	69.0
18	Maryland	39.0	162	1	76.5
19	Massachusetts	42.2	143	1	71.8

2. Extract X as all columns except the first column and Y as first column.

In [108]:

```
data.info()
data.shape
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 49 entries, 0 to 48
Data columns (total 5 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   State   49 non-null     object 
 1   Lat     49 non-null     float64
 2   Mort    49 non-null     int64  
 3   Ocean   49 non-null     int64  
 4   Long    49 non-null     float64
dtypes: float64(2), int64(2), object(1)
memory usage: 2.0+ KB
```

Out[108]:

```
(49, 5)
```

In [109]:

```
x = np.array(data['Lat']).reshape((-1,1))
print("LATITUTE ARRAY : ",x)
y = np.array(data['Mort'])
print("\nMORTAL ARRAY : ",y)
```

```
LATITUTE ARRAY :  [[33. ]
 [34.5]
 [35. ]
 [37.5]
 [39. ]
 [41.8]
 [39. ]
 [39. ]
 [28. ]
 [33. ]
 [44.5]
 [40. ]
 [40.2]
 [42.2]
 [38.5]
 [37.8]
 [31.2]
 [45.2]
 [39. ]
 [42.2]
 [43.5]
 [46. ]
 [32.8]
 [38.5]
 [47. ]
 [41.5]
 [39. ]
 [43.8]
 [40.2]
 [35. ]
 [43. ]
 [35.5]
 [47.5]
 [40.2]
 [35.5]
 [44. ]
 [40.8]
 [41.8]
 [33.8]
 [44.8]
 [36. ]
 [31.5]
 [39.5]
```

```
 [44. ]
 [37.5]
 [47.5]
 [38.8]
 [44.5]
 [43. ]]

MORTAL ARRAY :  [219 160 170 182 149 159 200 177 197 214 116 124 128 128 166 147 190 117
 162 143 117 116 207 131 109 122 191 129 159 141 152 199 115 131 182 136
 132 137 178  86 186 229 142 153 166 117 136 110 134]
```

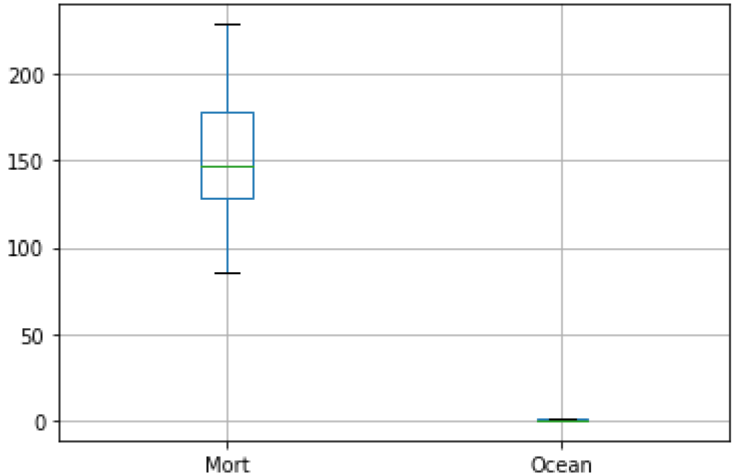
3. Visualize the dataset.

In [110]:

```
data.boxplot(column=["Mort", "Ocean"])
```

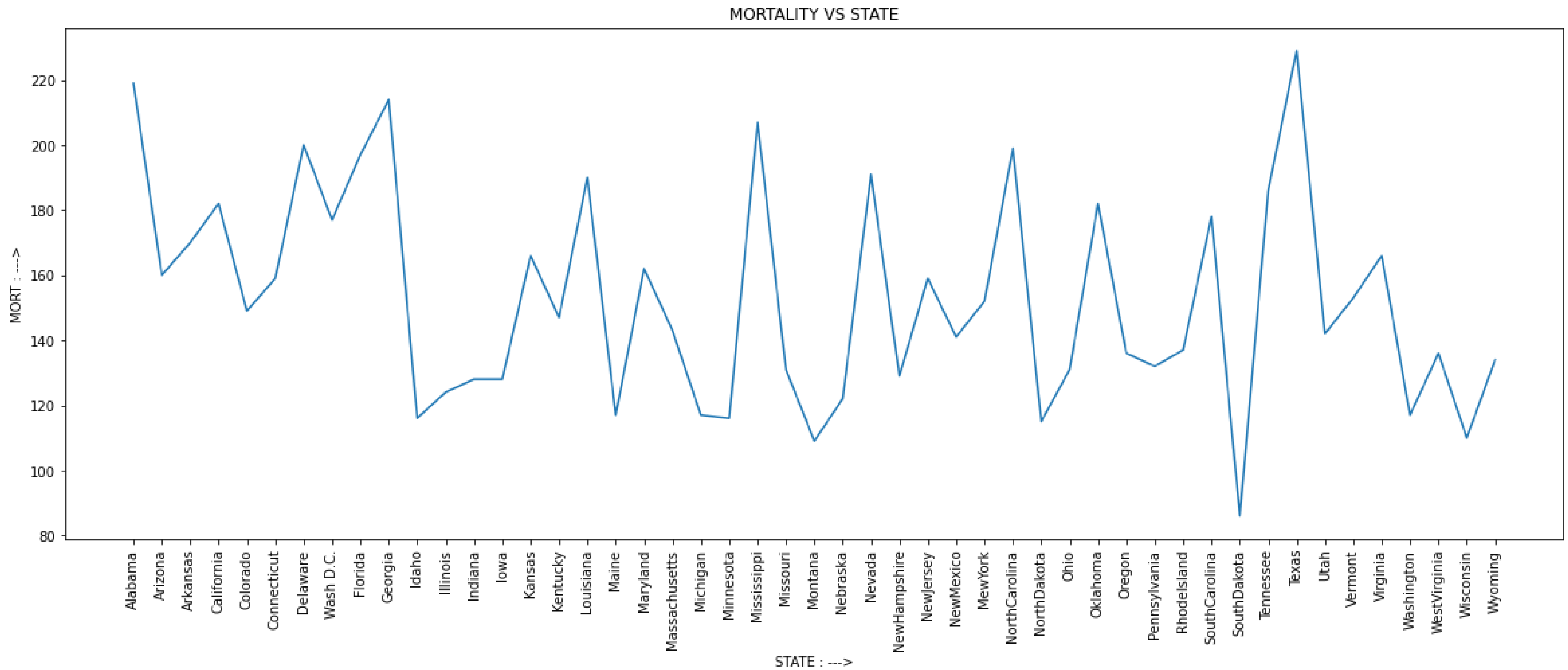
Out[110]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x23caa95e880>
```



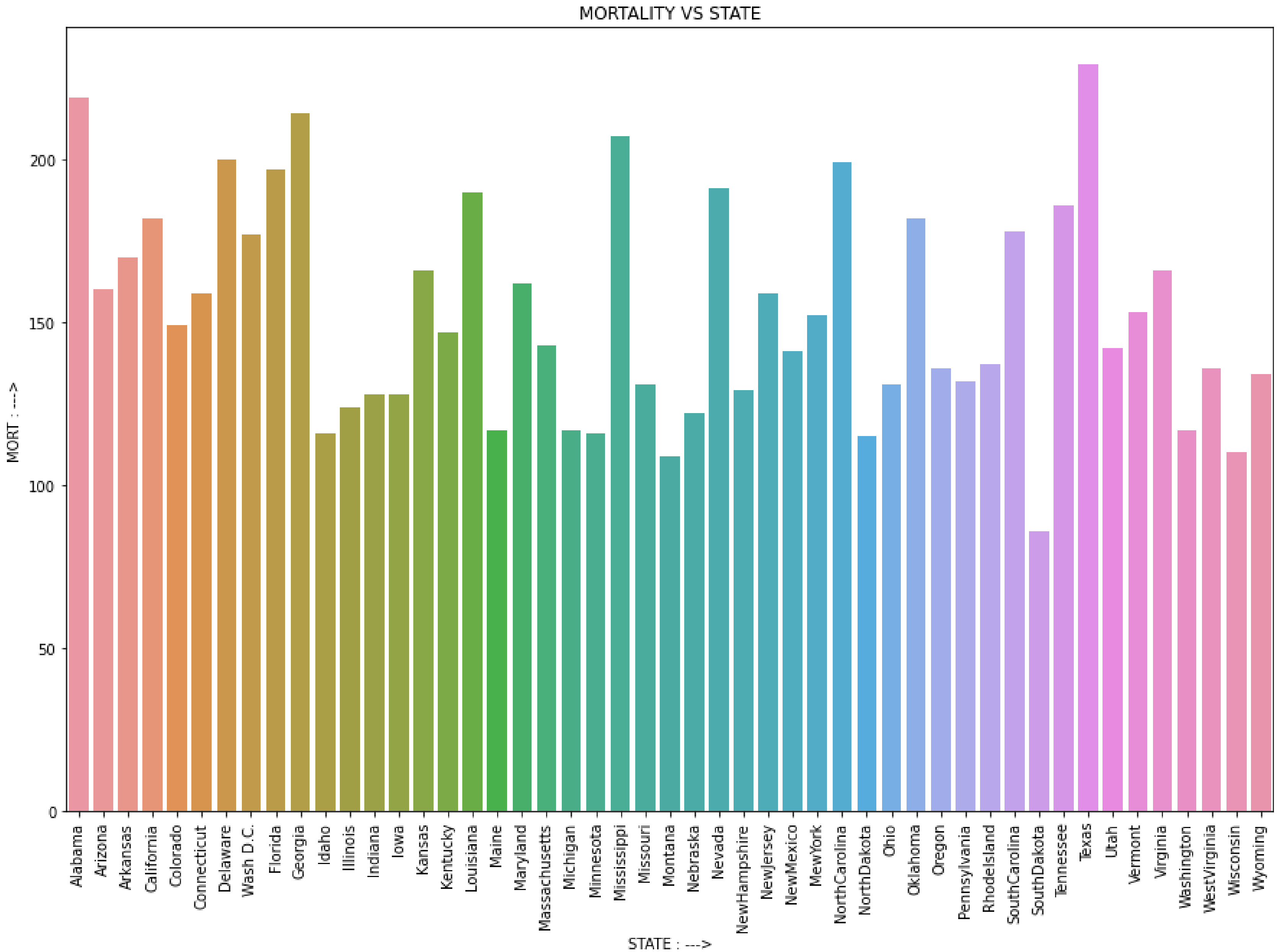
In [111]:

```
plt.figure(figsize = (20,7))
plt.plot(data["State"], data["Mort"])
plt.xticks(rotation = 90)
plt.xlabel("STATE : --->")
plt.ylabel("MORT : --->")
plt.title("MORTALITY VS STATE")
plt.show()
```



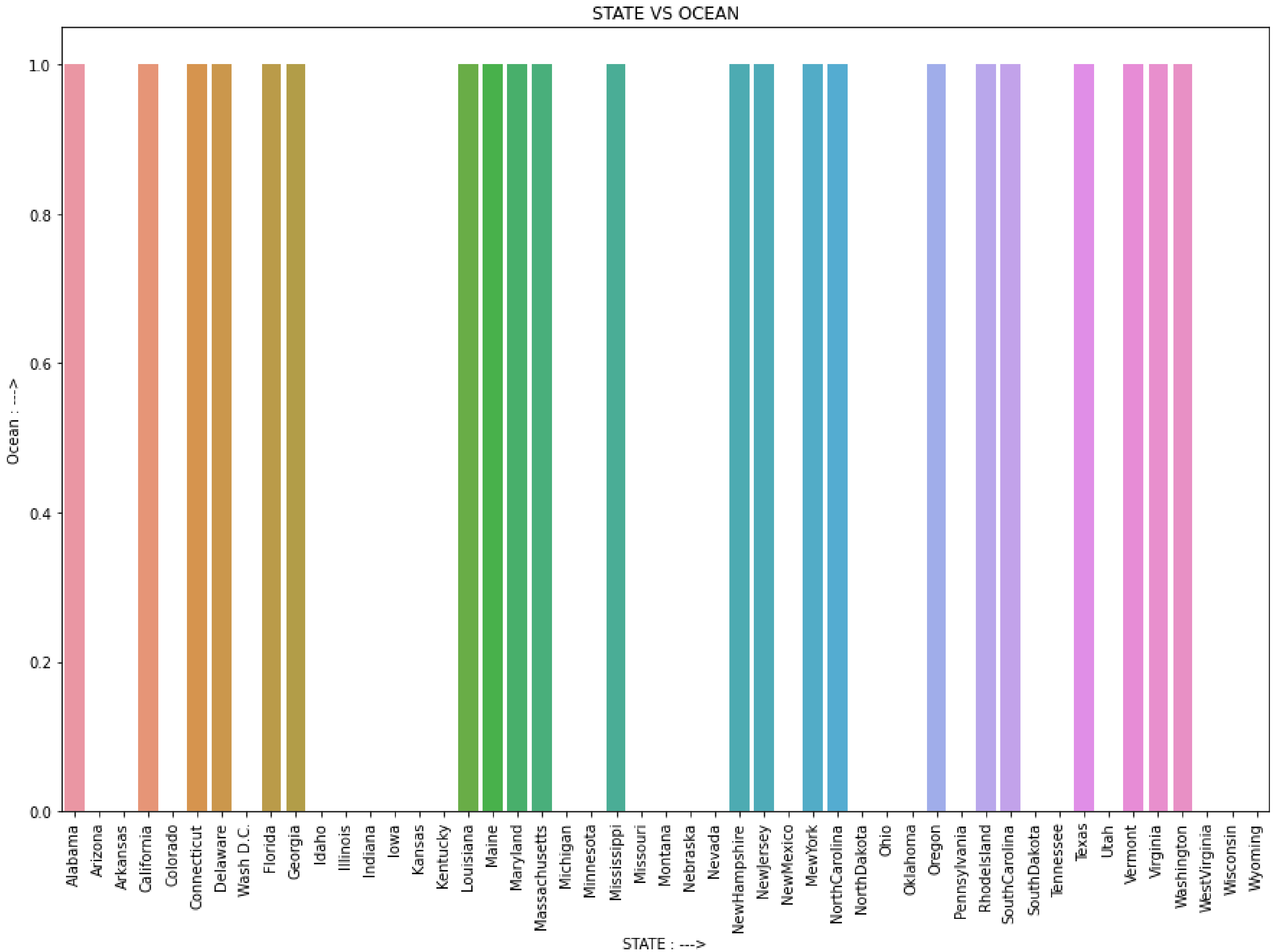
In [112]:

```
plt.figure(figsize = (15,10))
ax = sns.barplot(x=data["State"],y=data["Mort"])
plt.xticks(rotation = 90)
plt.xlabel("STATE : --->")
plt.ylabel("MORT : --->")
plt.title("MORTALITY VS STATE")
plt.show()
```


MORTALITY VS STATE
MORT : --->
0
50
100
150
200
Alabama
Arizona
Arkansas
California
Colorado
Connecticut
Delaware
Wash D.C.
Florida
Georgia
Idaho
Illinois
Indiana
Iowa
Kansas
Kentucky
Louisiana
Maine
Maryland
Massachusetts
Michigan
Minnesota
Mississippi
Missouri
Montana
Nebraska
Nevada
NewHampshire
NewJersey
NewMexico
MewYork
NorthCarolina
NorthDakota
Ohio
Oklahoma
Oregon
Pennsylvania
RhodeIsland
SouthCarolina
SouthDakota
Tennessee
Texas
Utah
Vermont
Virginia
Washington
WestVirginia
Wisconsin
Wyoming
STATE : --->

In [113]:

```
plt.figure(figsize = (15,10))
ax = sns.barplot(x=data["State"],y=data["Ocean"])
plt.xticks(rotation = 90)
plt.xlabel("STATE : --->")
plt.ylabel("Ocean : --->")
plt.title("STATE VS OCEAN")
plt.show()
```


STATE VS OCEAN
Ocean : --->
STATE : --->
1.0
0.8
0.6
0.4
0.2
0.0
Alabama
Arizona
Arkansas
California
Colorado
Connecticut
Delaware
Wash D.C.
Florida
Georgia
Idaho
Illinois
Indiana
Iowa
Kansas
Kentucky
Louisiana
Maine
Maryland
Massachusetts
Michigan
Minnesota
Mississippi
Missouri
Montana
Nebraska
Nevada
NewHampshire
NewJersey
NewMexico
NewYork
NorthCarolina
NorthDakota
Ohio
Oklahoma
Oregon
Pennsylvania
RhodeIsland
SouthCarolina
SouthDakota
Tennessee
Texas
Utah
Vermont
Virginia
Washington
WestVirginia
Wisconsin
Wyoming

4. Split the data into training set and testing set. Perform 10-fold cross validation.

Training Data:

5. Train a Logistic regression model for the dataset.

Performed 10-fold cross validation and found each fold accuracy and average accuracy

In [114]:

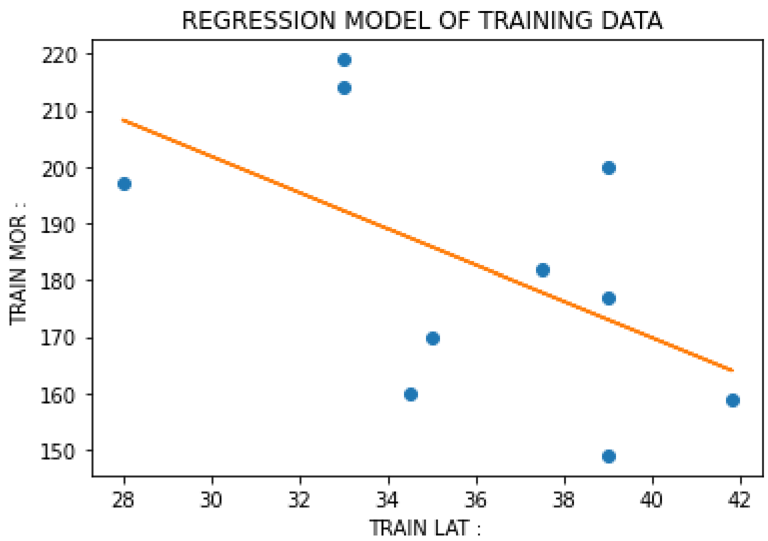
```
X = np.array(data['Lat']).reshape((-1,1))
Y = np.array(data['Mort'])
print("\nMORTAL ARRAY : ",y)
k = 10
kf = KFold(n_splits=k, random_state=None)
model = LogisticRegression(solver= 'liblinear')

acc_score = []

for train_index , test_index in kf.split(X):
    X_train , X_test = X[train_index],X[test_index]
    y_train , y_test = Y[train_index] , Y[test_index]

    model.fit(X_train,y_train)
    pred_values = model.predict(X_test)

    acc = accuracy_score(pred_values , y_test)
    acc_score.append(acc)

avg_acc_score = sum(acc_score)/k

print('\nACCURACY OF EACH FOLD - {}\n'.format(acc_score))
print('AVERAGE ACCURACY : {}'.format(avg_acc_score))
```

```
MORTAL ARRAY :  [219 160 170 182 149 159 200 177 197 214 116 124 128 128 166 147 190 117
 162 143 117 116 207 131 109 122 191 129 159 141 152 199 115 131 182 136
 132 137 178  86 186 229 142 153 166 117 136 110 134]

ACCURACY OF EACH FOLD - [0.0, 0.0, 0.0, 0.2, 0.2, 0.0, 0.0, 0.0, 0.0, 0.0]

AVERAGE ACCURACY : 0.04
```

In [115]:

```
x_train = np.array(data['Lat'].head(10)).reshape((-1,1))
y_train = np.array(data['Mort'].head(10))
model=LinearRegression().fit(x_train,y_train)
print("X_TEST :\n",x_train)
print("\nY_TEST : ",y_train)
print("\nCOEFFICIENT/SLOPE : ",model.coef_)
print("\nINTERCEPT : ",model.intercept_)
#plt.scatter(x_test,y_test)
plt.title('REGRESSION MODEL OF TRAINING DATA ')
plt.xlabel('TRAIN LAT : ')
plt.ylabel('TRAIN MOR : ')
plt.plot(x_train, y_train,'o')
plt.plot(x_train, model.coef_*x_train + model.intercept_)
plt.show()
```

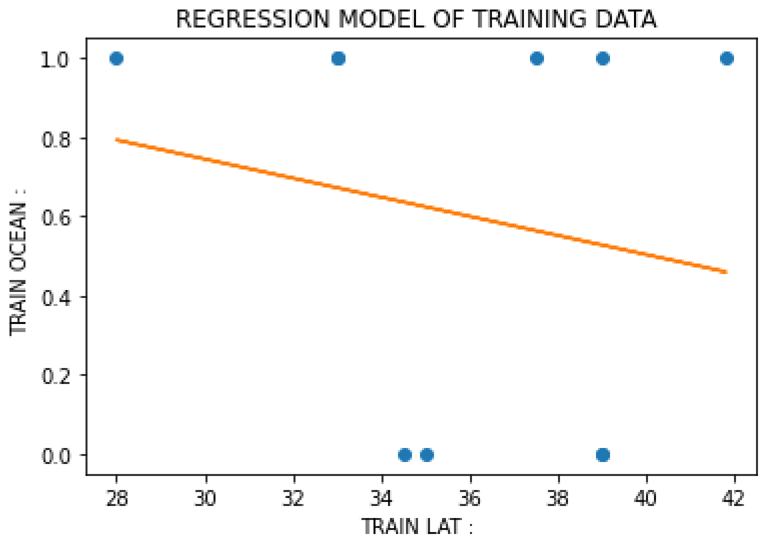
```
X_TEST :
 [[33. ]
 [34.5]
 [35. ]
 [37.5]
 [39. ]
 [41.8]
 [39. ]
 [39. ]
 [28. ]
 [33. ]]

Y_TEST :  [219 160 170 182 149 159 200 177 197 214]

COEFFICIENT/SLOPE :  [-3.20826808]

INTERCEPT :  298.1334854458065
```



In [116]:

```
x_train = np.array(data['Lat'].head(10)).reshape((-1,1))
y_train = np.array(data['Ocean'].head(10))
model=LinearRegression().fit(x_train,y_train)
print("X_TEST :\n",x_train)
print("\nY_TEST : ",y_train)
print("\nCOEFFICIENT/SLOPE : ",model.coef_)
print("\nINTERCEPT : ",model.intercept_)
#plt.scatter(x_test,y_test)
plt.title('REGRESSION MODEL OF TRAINING DATA ')
plt.xlabel('TRAIN LAT : ')
plt.ylabel('TRAIN OCEAN : ')
plt.plot(x_train, y_train,'o')
plt.plot(x_train, model.coef_*x_train + model.intercept_)
plt.show()
```

```
X_TEST :
 [[33. ]
 [34.5]
 [35. ]
 [37.5]
 [39. ]
 [41.8]
 [39. ]
 [39. ]
 [28. ]
 [33. ]]

Y_TEST :  [1 0 0 1 0 1 1 0 1 1]

COEFFICIENT/SLOPE :  [-0.02416698]

INTERCEPT :  1.4695280012961067
```



Test Data:

5. Train a Logistic regression model for the dataset.

6. Display the coefficients and form the logistic regression equation.

In [117]:

```
Splitx = np.array_split(data['Lat'],2)
Splity = np.array_split(data['Mort'],2)
x_test1 = np.array(Splitx[0]).reshape((-1,1))
y_test1 = np.array(Splity[0])
x_test1.reshape(-1,1)
model=LinearRegression().fit(x_test1,y_test1)
print("X_TEST :\n",x_test1)
print("\nY_TEST : ",y_test1)
print("\nCOEFFICIENT/SLOPE : ",model.coef_)
print("\nINTERCEPT : ",model.intercept_)
#plt.scatter(x_test,y_test)
plt.title('REGRESSION MODEL OF TEST DATA ')
plt.xlabel('TEST LAT : ')
plt.ylabel('TEST MOR : ')
plt.plot(x_test1, y_test1,'o')
plt.plot(x_test1, model.coef_*x_test1 + model.intercept_)
plt.show()
```

```
X_TEST :
 [[33. ]
 [34.5]
 [35. ]
 [37.5]
 [39. ]
 [41.8]
 [39. ]
 [39. ]
 [28. ]
 [33. ]
 [44.5]
 [40. ]
 [40.2]
 [42.2]
 [38.5]
 [37.8]
 [31.2]
 [45.2]
 [39. ]
 [42.2]
 [43.5]
 [46. ]
 [32.8]
 [38.5]
 [47. ]]

Y_TEST :  [219 160 170 182 149 159 200 177 197 214 116 124 128 128 166 147 190 117
 162 143 117 116 207 131 109]

COEFFICIENT/SLOPE :  [-5.90303393]

INTERCEPT :  385.7799224237401
```

7 Compute the accuracy and confusion matrix.

ACCURACY :

In [118]:

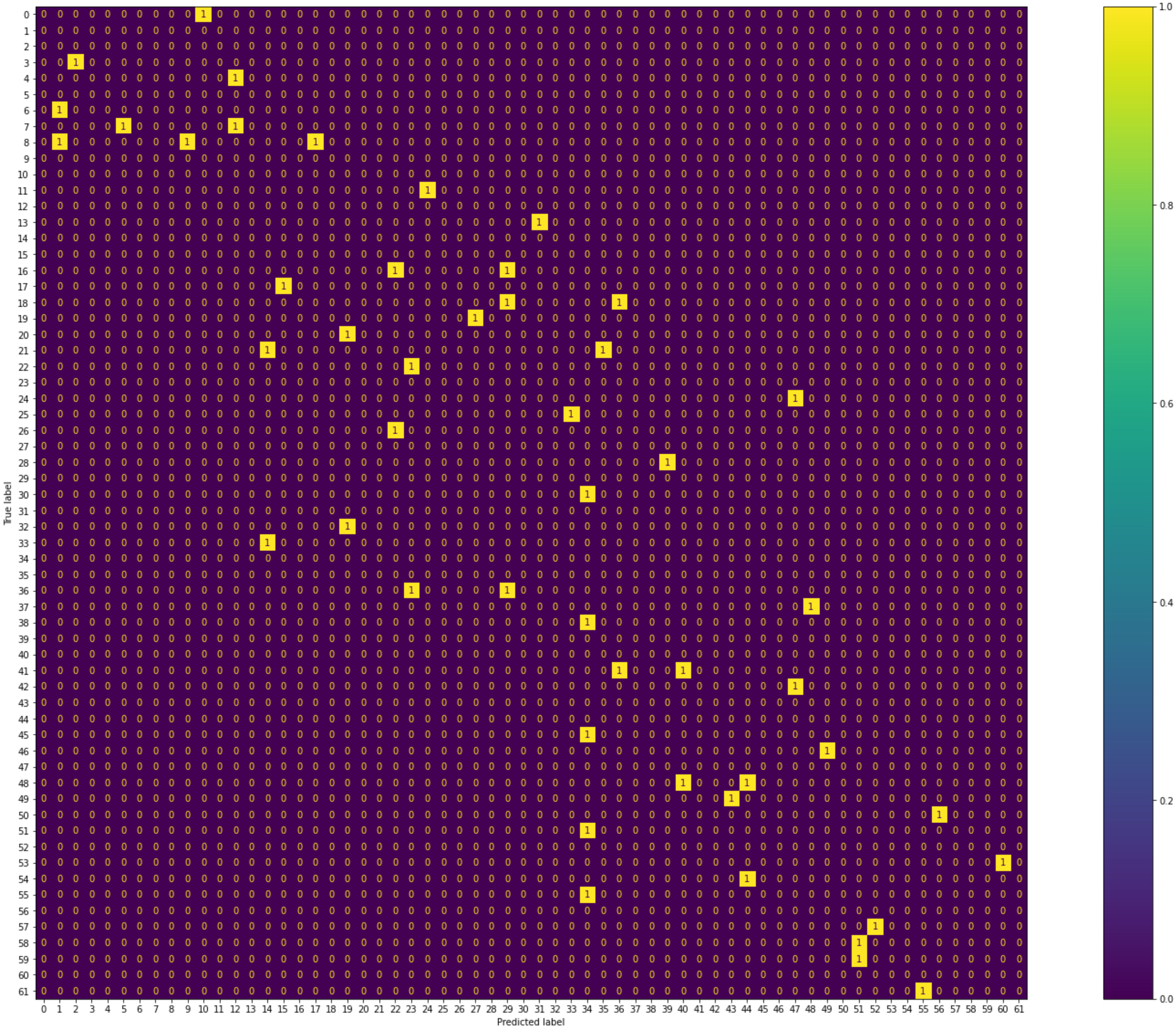
```
Splitx = np.array_split(data['Lat'],1)
Splity = np.array_split(data['Mort'],1)
x_rest = np.array(Splitx[0]).reshape((-1,1))
print(x_rest)
y_true = np.array(Splity[0])
print(y_true)
y_pred = np.array((model.predict(x_rest)))
y_pred = y_pred.round(decimals=0)
print(y_pred)
fig, ax = plt.subplots(figsize=(30, 20))
cm = confusion_matrix(y_true, y_pred)
print("\nCONFUSION MATRIX (2D) : \n",cm)
#tp, fn, fp, tn = confusion_matrix(y_true,y_pred,labels=[0,1]).reshape(-1)
#print('Outcome values : \n', tp, fn, fp, tn)
# classification report for precision, recall f1-score and accuracy
matrix = classification_report(y_true,y_pred)
print('\nCONFUSION MATRIX CLASSIFICATION REPORT INCLUDE ALL ATTRIBUTES OF CM : \n',matrix)
print("\nCONFUSION MATRIX GRAPH:\n")
cm_display = ConfusionMatrixDisplay(cm).plot(ax=ax)
```

```
[[33. ]
 [34.5]
 [35. ]
 [37.5]
 [39. ]
 [41.8]
 [39. ]
 [39. ]
 [28. ]
 [33. ]
 [44.5]
 [40. ]
 [40.2]
 [42.2]
 [38.5]
 [37.8]
 [31.2]
 [45.2]
 [39. ]
 [42.2]
 [43.5]
 [46. ]
 [32.8]
 [38.5]
 [47. ]
 [41.5]
 [39. ]
 [43.8]
 [40.2]
 [35. ]
 [43. ]
 [35.5]
 [47.5]
 [40.2]
 [35.5]
 [44. ]
 [40.8]
 [41.8]
 [33.8]
 [44.8]
 [36. ]
 [31.5]
 [39.5]
```

```
 [44. ]
 [37.5]
 [47.5]
 [38.8]
 [44.5]
 [43. ]]
[219 160 170 182 149 159 200 177 197 214 116 124 128 128 166 147 190 117
 162 143 117 116 207 131 109 122 191 129 159 141 152 199 115 131 182 136
 132 137 178  86 186 229 142 153 166 117 136 110 134]
[191. 182. 179. 164. 156. 139. 156. 156. 220. 191. 123. 150. 148. 137.
 159. 163. 202. 119. 156. 137. 129. 114. 192. 159. 108. 141. 156. 127.
 148. 179. 132. 176. 105. 148. 176. 126. 145. 139. 186. 121. 173. 200.
 153. 126. 164. 105. 157. 123. 132.]

CONFUSION MATRIX (2D) :
 [[0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 ...
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]]

CONFUSION MATRIX CLASSIFICATION REPORT INCLUDE ALL ATTRIBUTES OF CM :
               precision    recall  f1-score   support

        86.0       0.00      0.00      0.00       1.0
       105.0       0.00      0.00      0.00       0.0
       108.0       0.00      0.00      0.00       0.0
       109.0       0.00      0.00      0.00       1.0
       110.0       0.00      0.00      0.00       1.0
       114.0       0.00      0.00      0.00       0.0
       115.0       0.00      0.00      0.00       1.0
       116.0       0.00      0.00      0.00       2.0
       117.0       0.00      0.00      0.00       3.0
       119.0       0.00      0.00      0.00       0.0
       121.0       0.00      0.00      0.00       0.0
       122.0       0.00      0.00      0.00       1.0
       123.0       0.00      0.00      0.00       0.0
       124.0       0.00      0.00      0.00       1.0
       126.0       0.00      0.00      0.00       0.0
       127.0       0.00      0.00      0.00       0.0
       128.0       0.00      0.00      0.00       2.0
```

129.0	0.00	0.00	0.00	1.0
131.0	0.00	0.00	0.00	2.0
132.0	0.00	0.00	0.00	1.0
134.0	0.00	0.00	0.00	1.0
136.0	0.00	0.00	0.00	2.0
137.0	0.00	0.00	0.00	1.0
139.0	0.00	0.00	0.00	0.0
141.0	0.00	0.00	0.00	1.0
142.0	0.00	0.00	0.00	1.0
143.0	0.00	0.00	0.00	1.0
145.0	0.00	0.00	0.00	0.0
147.0	0.00	0.00	0.00	1.0
148.0	0.00	0.00	0.00	0.0
149.0	0.00	0.00	0.00	1.0
150.0	0.00	0.00	0.00	0.0
152.0	0.00	0.00	0.00	1.0
153.0	0.00	0.00	0.00	1.0
156.0	0.00	0.00	0.00	0.0
157.0	0.00	0.00	0.00	0.0
159.0	0.00	0.00	0.00	2.0
160.0	0.00	0.00	0.00	1.0
162.0	0.00	0.00	0.00	1.0
163.0	0.00	0.00	0.00	0.0
164.0	0.00	0.00	0.00	0.0
166.0	0.00	0.00	0.00	2.0
170.0	0.00	0.00	0.00	1.0
173.0	0.00	0.00	0.00	0.0
176.0	0.00	0.00	0.00	0.0
177.0	0.00	0.00	0.00	1.0
178.0	0.00	0.00	0.00	1.0
179.0	0.00	0.00	0.00	0.0
182.0	0.00	0.00	0.00	2.0
186.0	0.00	0.00	0.00	1.0
190.0	0.00	0.00	0.00	1.0
191.0	0.00	0.00	0.00	1.0
192.0	0.00	0.00	0.00	0.0
197.0	0.00	0.00	0.00	1.0
199.0	0.00	0.00	0.00	1.0
200.0	0.00	0.00	0.00	1.0
202.0	0.00	0.00	0.00	0.0
207.0	0.00	0.00	0.00	1.0
214.0	0.00	0.00	0.00	1.0
219.0	0.00	0.00	0.00	1.0

```
       220.0       0.00      0.00      0.00       0.0
       229.0       0.00      0.00      0.00       1.0

    accuracy                           0.00      49.0
   macro avg       0.00      0.00      0.00      49.0
weighted avg       0.00      0.00      0.00      49.0


CONFUSION MATRIX GRAPH:
```


True label
Predicted label
1.0
0.8
0.6
0.4
0.2
0.0

8 Display the correlation between all the attributes.

In [119]:

```
x_test1 = np.array(data['Lat'])
y_test1 = np.array(data['Mort'])
corr_matrix= np.corrcoef(x_test1,y_test1)
print("CORRELATION COEFFICIENT FOR LAT AND MORT : \n\n", corr_matrix)
```

```
CORRELATION COEFFICIENT FOR LAT AND MORT :

 [[ 1.         -0.82451779]
 [-0.82451779  1.        ]]
```

In [120]:

```
x_test1 = np.array(data['Lat'])
y_test1 = np.array(data['Ocean'])
corr_matrix= np.corrcoef(x_test1,y_test1)
print("CORRELATION COEFFICIENT FOR LAT AND OCEAN : \n\n", corr_matrix)
```

```
CORRELATION COEFFICIENT FOR LAT AND OCEAN :

 [[ 1.         -0.21954196]
 [-0.21954196  1.        ]]
```

In [121]:

```
x_test1 = np.array(data['Mort'])
y_test1 = np.array(data['Ocean'])
corr_matrix= np.corrcoef(x_test1,y_test1)
print("CORRELATION COEFFICIENT FOR MORT AND OCEAN : \n\n", corr_matrix)
```

```
CORRELATION COEFFICIENT FOR MORT AND OCEAN :

 [[1.        0.4733547]
 [0.4733547 1.       ]]
```

THANK YOU

In [ ]: