Salary Prediction

In [221]:

```
#Imported all necessary library
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [222]:

```
#Read the csv file
salary_pre_data = pd.read_csv('salary.csv')
salary_pre_data.head()
```

Out[222]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Fe

In [223]:

```
salary_pre_data[salary_pre_data.duplicated()].shape
```

Out[223]:

```
(24, 15)
```

Data Cleaning

In [224]:

```
salary_pre_data.drop_duplicates(keep = 'first',inplace=True)
```

In [225]:

```
salary_pre_data[salary_pre_data.duplicated()].shape
```

Out[225]:

```
(0, 15)
```

First study the Dataset then decide/select which feature are useful to train our model or not.Take those feature to train model and drop necessary feature. .

In [226]:

```
salary_pre_data.drop(['fnlwgt','education-num','capital-gain','capital-loss','race','relati
salary_pre_data.head()
```

Out[226]:

	age	workclass	education	marital-status	occupation	sex	hours-per-week	native-country	salary
0	39	State-gov	Bachelors	Never-married	Adm-clerical	Male	40	United-States	<=50K
1	50	Self-emp-not-inc	Bachelors	Married-civ-spouse	Exec-managerial	Male	13	United-States	<=50K
2	38	Private	HS-grad	Divorced	Handlers-cleaners	Male	40	United-States	<=50K
3	53	Private	11th	Married-civ-spouse	Handlers-cleaners	Male	40	United-States	<=50K
4	28	Private	Bachelors	Married-civ-spouse	Prof-specialty	Female	40	Cuba	<=50K

In [227]:

```
salary_pre_data.columns
```

Out[227]:

```
Index(['age', 'workclass', 'education', 'marital-status', 'occupation', 'se
x',
       'hours-per-week', 'native-country', 'salary'],
      dtype='object')
```

In [228]:

```
salary_pre_data.rename({'age':'Age', 'workclass':'Employee_Type','education':'Education','m
salary_pre_data.head()
```

Out[228]:

	Age	Employee_Type	Education	Marital_Status	Occupation	Gender	Hours_Per_Week	Nati
0	39	State-gov	Bachelors	Never-married	Adm-clerical	Male	40	U
1	50	Self-emp-not-inc	Bachelors	Married-civ-spouse	Exec-managerial	Male	13	U
2	38	Private	HS-grad	Divorced	Handlers-cleaners	Male	40	U
3	53	Private	11th	Married-civ-spouse	Handlers-cleaners	Male	40	U
4	28	Private	Bachelors	Married-civ-spouse	Prof-specialty	Female	40	

In [229]:

```
salary_pre_data.shape
```

Out[229]:

```
(32537, 9)
```

In [230]:

```
salary_pre_data['Employee_Type'].value_counts()
```

Out[230]:

```
 Private             22673
 Self-emp-not-inc     2540
 Local-gov            2093
 ?                    1836
 State-gov            1298
 Self-emp-inc         1116
 Federal-gov           960
 Without-pay            14
 Never-worked            7
Name: Employee_Type, dtype: int64
```

In [231]:

```
#here we replace the string by unkonwn string
salary_pre_data['Employee_Type'] = salary_pre_data['Employee_Type'].str.replace('?','Privat
```

In [232]:

```
salary_pre_data['Employee_Type'].value_counts()
```

Out[232]:

```
 Private             24509
 Self-emp-not-inc     2540
 Local-gov            2093
 State-gov            1298
 Self-emp-inc         1116
 Federal-gov           960
 Without-pay            14
 Never-worked            7
Name: Employee_Type, dtype: int64
```

In [233]:

```
salary_pre_data['Education'].value_counts()
```

Out[233]:

```
 HS-grad         10494
 Some-college     7282
 Bachelors        5353
 Masters          1722
 Assoc-voc        1382
 11th             1175
 Assoc-acdm       1067
 10th              933
 7th-8th           645
 Prof-school       576
 9th               514
 12th              433
 Doctorate         413
 5th-6th           332
 1st-4th           166
 Preschool          50
Name: Education, dtype: int64
```

In [234]:

```
salary_pre_data['Education'].unique()
```

Out[234]:

```
array([' Bachelors', ' HS-grad', ' 11th', ' Masters', ' 9th',
       ' Some-college', ' Assoc-acdm', ' Assoc-voc', ' 7th-8th',
       ' Doctorate', ' Prof-school', ' 5th-6th', ' 10th', ' 1st-4th',
       ' Preschool', ' 12th'], dtype=object)
```

In [235]:

```
#here we make group of education
salary_pre_data['Education'].replace([' 11th',' 9th', ' Some-college','7th-8th', ' 5th-6th'
```

In [236]:

```
#here we make group of education
salary_pre_data['Education'].replace([' Assoc-acdm', ' Assoc-voc',' Prof-school',' Some-col
```

In [237]:

```
salary_pre_data['Education'].unique()
```

Out[237]:

```
array([' Bachelors', ' HS-grad', 'School Education', ' Masters',
       'Higher Education', ' School Education', ' Doctorate'],
      dtype=object)
```

In [238]:

```
salary_pre_data['Marital_Status'].value_counts()
```

Out[238]:

```
 Married-civ-spouse       14970
 Never-married            10667
 Divorced                  4441
 Separated                 1025
 Widowed                    993
 Married-spouse-absent      418
 Married-AF-spouse           23
Name: Marital_Status, dtype: int64
```

In [239]:

```
#here we make group of married employee
salary_pre_data['Marital_Status'].replace(['Married-civ-spouse','Married-AF-spouse'],'Marri
```

In [240]:

```
#here we make group of single or unmarried employee
salary_pre_data['Marital_Status'].replace(['Never-married','Divorced','Separated','Widowed'
```

In [241]:

```
salary_pre_data['Marital_Status'].value_counts()
```

Out[241]:

```
 other      17544
 Married    14993
Name: Marital_Status, dtype: int64
```

In [242]:

```
salary_pre_data['Occupation'].value_counts()
```

Out[242]:

```
 Prof-specialty       4136
 Craft-repair         4094
 Exec-managerial      4065
 Adm-clerical         3768
 Sales                3650
 Other-service        3291
 Machine-op-inspct    2000
 ?                    1843
 Transport-moving     1597
 Handlers-cleaners    1369
 Farming-fishing       992
 Tech-support          927
 Protective-serv       649
 Priv-house-serv       147
 Armed-Forces            9
Name: Occupation, dtype: int64
```

In [243]:

```
#here we replace the string by unkonwn string
salary_pre_data['Occupation'] = salary_pre_data['Occupation'].str.replace('?','Prof-special
```

In [244]:

```
salary_pre_data['Occupation'].value_counts()
```

Out[244]:

```
 Prof-specialty       5979
 Craft-repair         4094
 Exec-managerial      4065
 Adm-clerical         3768
 Sales                3650
 Other-service        3291
 Machine-op-inspct    2000
 Transport-moving     1597
 Handlers-cleaners    1369
 Farming-fishing       992
 Tech-support          927
 Protective-serv       649
 Priv-house-serv       147
 Armed-Forces            9
Name: Occupation, dtype: int64
```

In [245]:

```
salary_pre_data['Gender'].value_counts()
```

Out[245]:

```
 Male      21775
 Female    10762
Name: Gender, dtype: int64
```

In [246]:

```
salary_pre_data['Hours_Per_Week'].value_counts()
```

Out[246]:

```
40    15204
50     2817
45     1823
60     1475
35     1296
      ...  
82        1
92        1
87        1
74        1
94        1
Name: Hours_Per_Week, Length: 94, dtype: int64
```

In [247]:

```
salary_pre_data['Native_Country'].value_counts()
```

Out[247]:

```
 United-States                 29153
 Mexico                          639
 ?                               582
 Philippines                     198
 Germany                         137
 Canada                          121
 Puerto-Rico                     114
 El-Salvador                     106
 India                           100
 Cuba                             95
 England                          90
 Jamaica                          81
 South                            80
 China                            75
 Italy                            73
 Dominican-Republic               70
 Vietnam                          67
 Japan                            62
 Guatemala                        62
 Poland                           60
 Columbia                         59
 Taiwan                           51
 Haiti                            44
 Iran                             43
 Portugal                         37
 Nicaragua                        34
 Peru                             31
 France                           29
 Greece                           29
 Ecuador                          28
 Ireland                          24
 Hong                             20
 Cambodia                         19
 Trinadad&Tobago                  19
 Laos                             18
 Thailand                         18
 Yugoslavia                       16
 Outlying-US(Guam-USVI-etc)       14
 Honduras                         13
 Hungary                          13
 Scotland                         12
 Holand-Netherlands                1
Name: Native_Country, dtype: int64
```

In [248]:

```
#here we replace the string by unkonwn string
salary_pre_data['Native_Country'] = salary_pre_data['Native_Country'].str.replace('?','Unit
```

In [249]:

```
salary_pre_data['Native_Country'].value_counts()
```

Out[249]:

```
 United-States                 29735
 Mexico                          639
 Philippines                     198
 Germany                         137
 Canada                          121
 Puerto-Rico                     114
 El-Salvador                     106
 India                           100
 Cuba                             95
 England                          90
 Jamaica                          81
 South                            80
 China                            75
 Italy                            73
 Dominican-Republic               70
 Vietnam                          67
 Japan                            62
 Guatemala                        62
 Poland                           60
 Columbia                         59
 Taiwan                           51
 Haiti                            44
 Iran                             43
 Portugal                         37
 Nicaragua                        34
 Peru                             31
 France                           29
 Greece                           29
 Ecuador                          28
 Ireland                          24
 Hong                             20
 Cambodia                         19
 Trinadad&Tobago                  19
 Laos                             18
 Thailand                         18
 Yugoslavia                       16
 Outlying-US(Guam-USVI-etc)       14
 Honduras                         13
 Hungary                          13
 Scotland                         12
 Holand-Netherlands                1
Name: Native_Country, dtype: int64
```

In [250]:

```
salary_pre_data['Salary'].value_counts()
```

Out[250]:

```
 <=50K    24698
 >50K      7839
Name: Salary, dtype: int64
```

In [251]:

```
salary_pre_data.head()
```

Out[251]:

	Age	Employee_Type	Education	Marital_Status	Occupation	Gender	Hours_Per_Week	Nati
0	39	State-gov	Bachelors	other	Adm-clerical	Male	40	U
1	50	Self-emp-not-inc	Bachelors	Married	Exec-managerial	Male	13	U
2	38	Private	HS-grad	other	Handlers-cleaners	Male	40	U
3	53	Private	School Education	Married	Handlers-cleaners	Male	40	U
4	28	Private	Bachelors	Married	Prof-specialty	Female	40	

In [252]:

```
salary_pre_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 32537 entries, 0 to 32560
Data columns (total 9 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   Age             32537 non-null  int64 
 1   Employee_Type   32537 non-null  object
 2   Education       32537 non-null  object
 3   Marital_Status  32537 non-null  object
 4   Occupation      32537 non-null  object
 5   Gender          32537 non-null  object
 6   Hours_Per_Week  32537 non-null  int64 
 7   Native_Country  32537 non-null  object
 8   Salary          32537 non-null  object
dtypes: int64(2), object(7)
memory usage: 2.5+ MB
```

In [253]:

```
salary_pre_data.isnull().sum()
```

Out[253]:

```
Age               0
Employee_Type     0
Education         0
Marital_Status    0
Occupation        0
Gender            0
Hours_Per_Week    0
Native_Country    0
Salary            0
dtype: int64
```

In [254]:

```
salary_pre_data.nunique()
```

Out[254]:

```
Age               73
Employee_Type      8
Education          7
Marital_Status     2
Occupation        14
Gender             2
Hours_Per_Week    94
Native_Country    41
Salary             2
dtype: int64
```

Exploratory Data Analysis

In [255]:

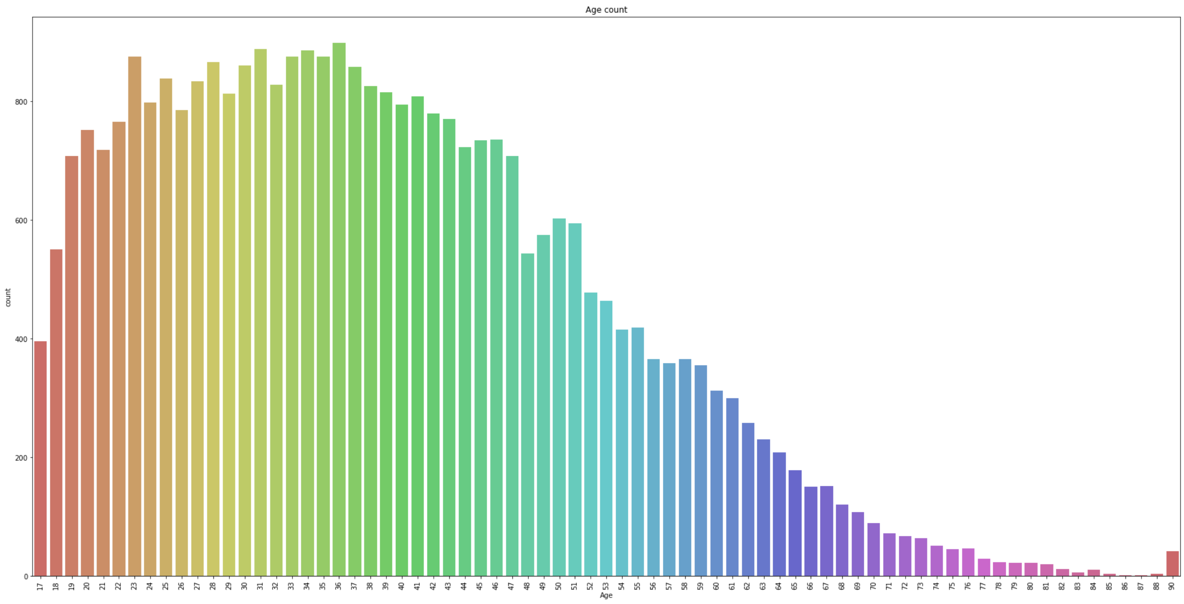
```
salary_pre_data['Age'].value_counts()
```

Out[255]:

```
36    898
31    888
34    886
23    876
33    875
     ...
83      6
88      3
85      3
86      1
87      1
Name: Age, Length: 73, dtype: int64
```

In [256]:

```
plt.figure(figsize=(30,15))
sns.countplot(salary_pre_data['Age'],data=salary_pre_data,palette='hls')
plt.xticks(rotation = 90)
plt.title('Age count')
plt.show()
```



In [257]:

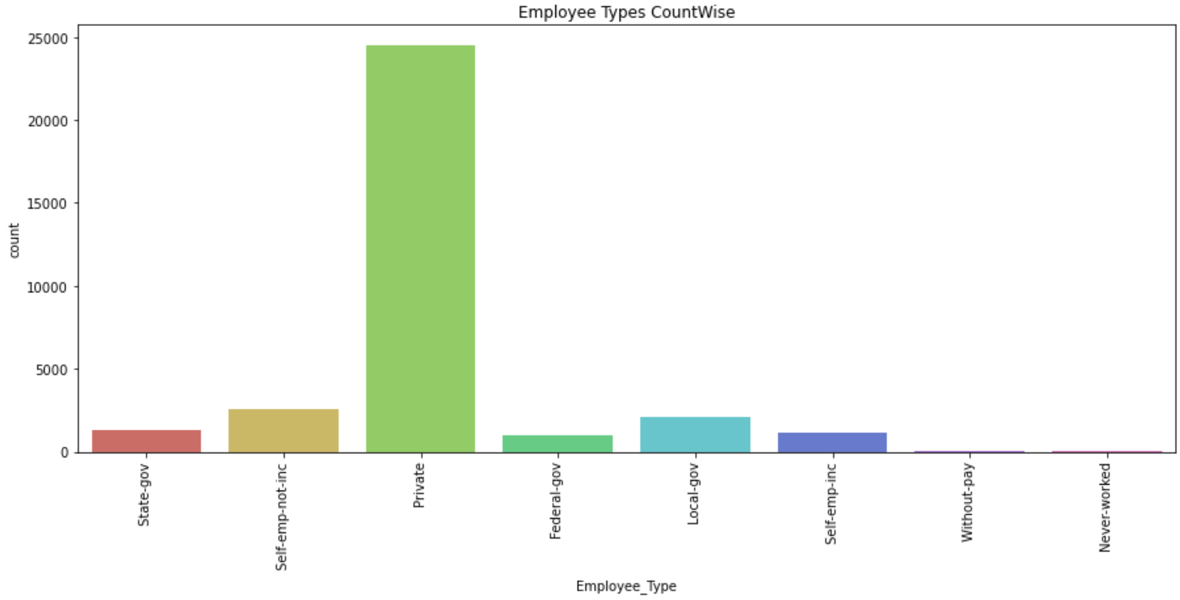
```
salary_pre_data['Employee_Type'].value_counts()
```

Out[257]:

```
 Private             24509
 Self-emp-not-inc     2540
 Local-gov            2093
 State-gov            1298
 Self-emp-inc         1116
 Federal-gov           960
 Without-pay            14
 Never-worked            7
Name: Employee_Type, dtype: int64
```

In [258]:

```
plt.figure(figsize=(15,6))
sns.countplot(salary_pre_data['Employee_Type'],data=salary_pre_data,palette='hls')
plt.xticks(rotation = 90)
plt.title('Employee Types CountWise')
plt.show()
```



In [259]:

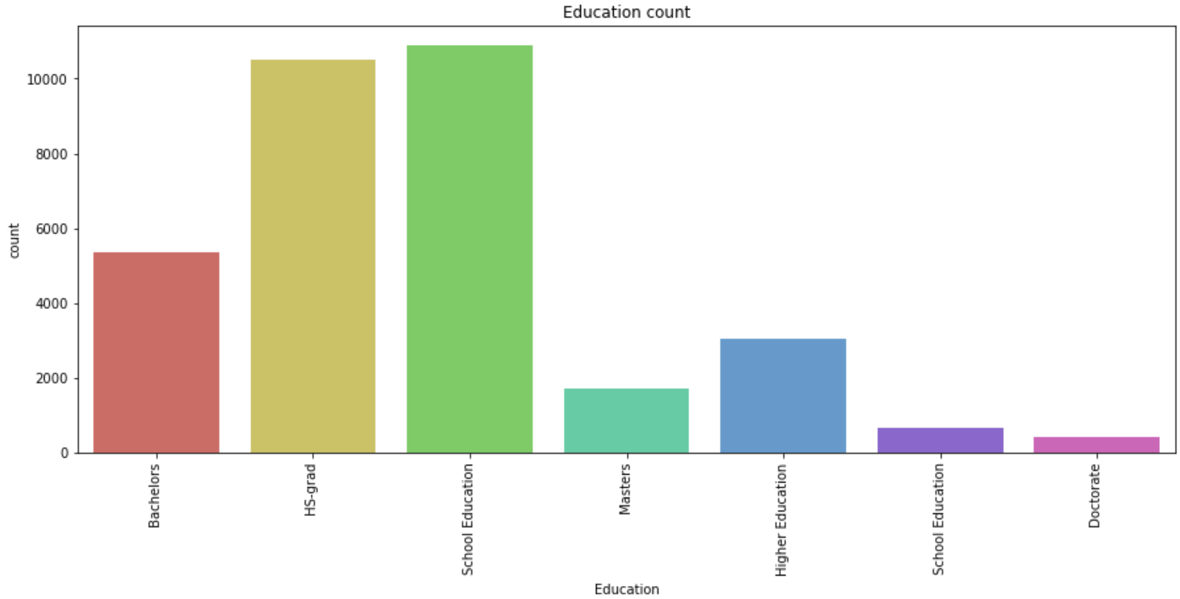
```
salary_pre_data['Education'].value_counts()
```

Out[259]:

```
School Education     10885
 HS-grad             10494
 Bachelors            5353
Higher Education      3025
 Masters              1722
 School Education      645
 Doctorate             413
Name: Education, dtype: int64
```

In [260]:

```
plt.figure(figsize=(15,6))
sns.countplot(salary_pre_data['Education'],data=salary_pre_data,palette='hls')
plt.xticks(rotation = 90)
plt.title('Education count')
plt.show()
```



In [261]:

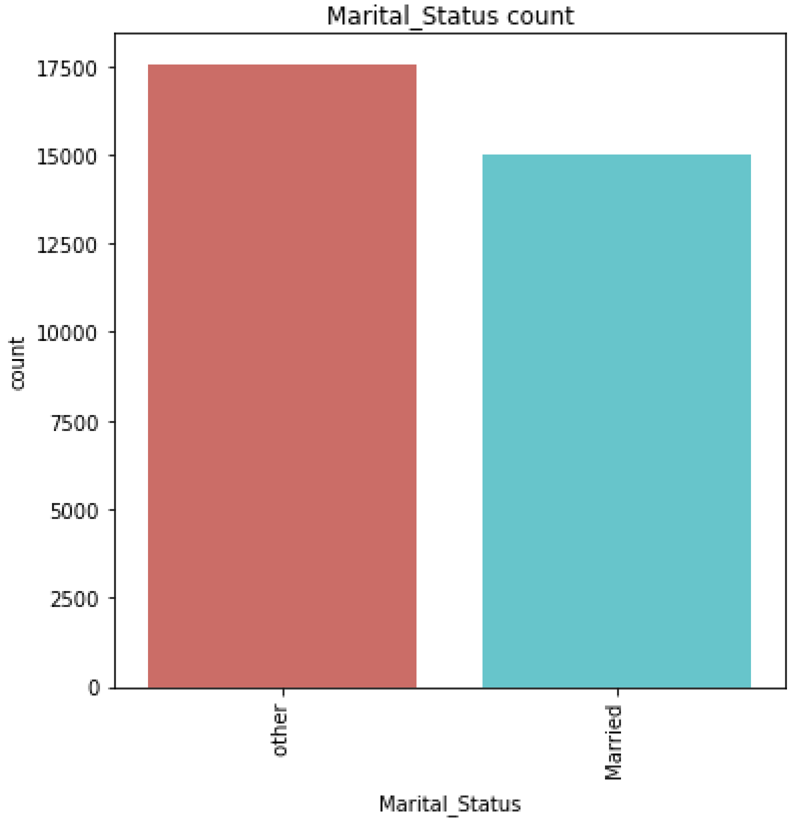
```
salary_pre_data['Marital_Status'].value_counts()
```

Out[261]:

```
 other      17544
 Married    14993
Name: Marital_Status, dtype: int64
```

In [262]:

```
plt.figure(figsize=(6,6))
sns.countplot(salary_pre_data['Marital_Status'],data=salary_pre_data,palette='hls')
plt.xticks(rotation = 90)
plt.title('Marital_Status count')
plt.show()
```



In [263]:

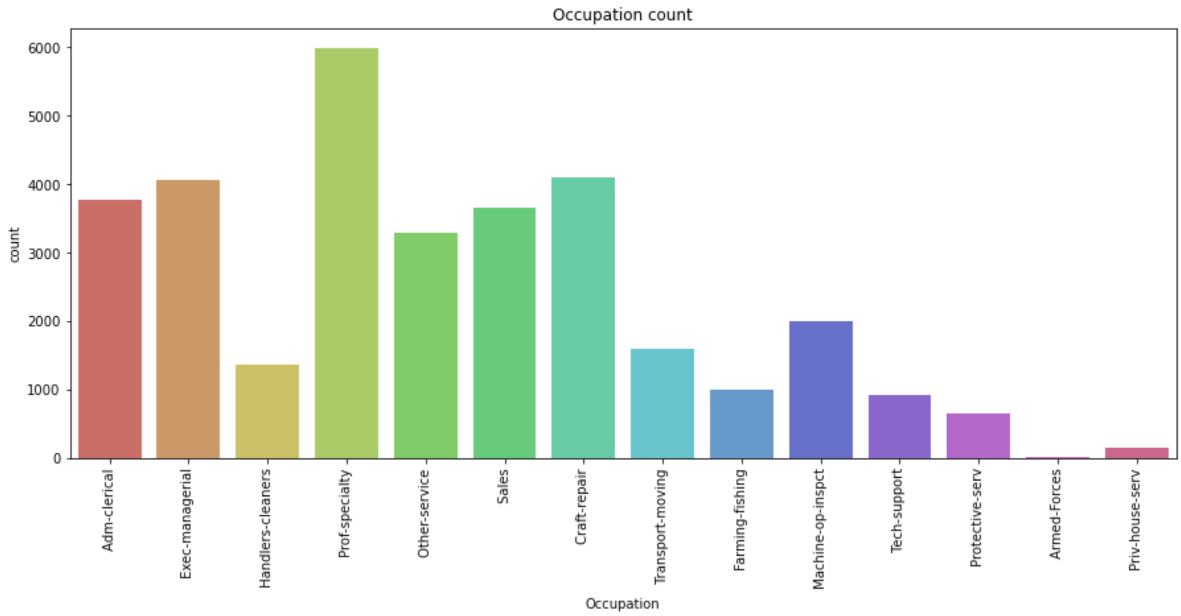
```
salary_pre_data['Occupation'].value_counts()
```

Out[263]:

```
 Prof-specialty       5979
 Craft-repair         4094
 Exec-managerial      4065
 Adm-clerical         3768
 Sales                3650
 Other-service        3291
 Machine-op-inspct    2000
 Transport-moving     1597
 Handlers-cleaners    1369
 Farming-fishing       992
 Tech-support          927
 Protective-serv       649
 Priv-house-serv       147
 Armed-Forces            9
Name: Occupation, dtype: int64
```

In [264]:

```
plt.figure(figsize=(15,6))
sns.countplot(salary_pre_data['Occupation'],data=salary_pre_data,palette='hls')
plt.xticks(rotation = 90)
plt.title('Occupation count')
plt.show()
```



In [265]:

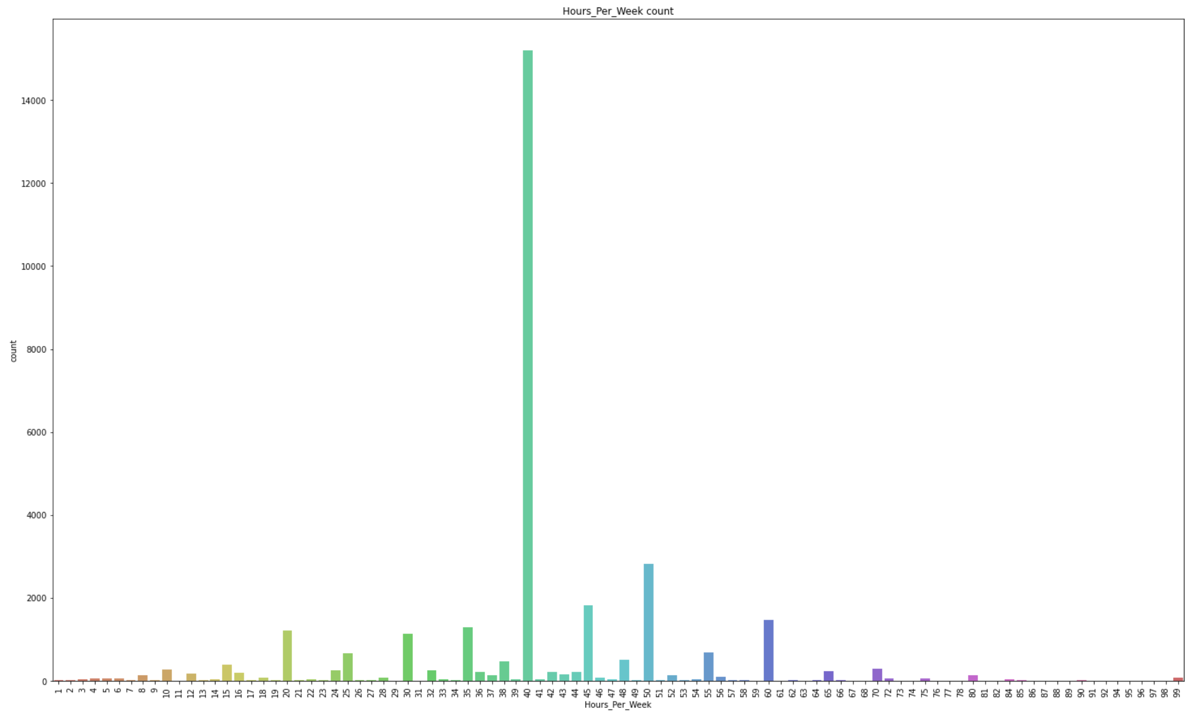
```
salary_pre_data['Hours_Per_Week'].value_counts()
```

Out[265]:

```
40    15204
50     2817
45     1823
60     1475
35     1296
      ...
82        1
92        1
87        1
74        1
94        1
Name: Hours_Per_Week, Length: 94, dtype: int64
```

In [266]:

```
plt.figure(figsize=(25,15))
sns.countplot(salary_pre_data['Hours_Per_Week'],data=salary_pre_data,palette='hls')
plt.xticks(rotation = 90)
plt.title('Hours_Per_Week count')
plt.show()
```



In [267]:

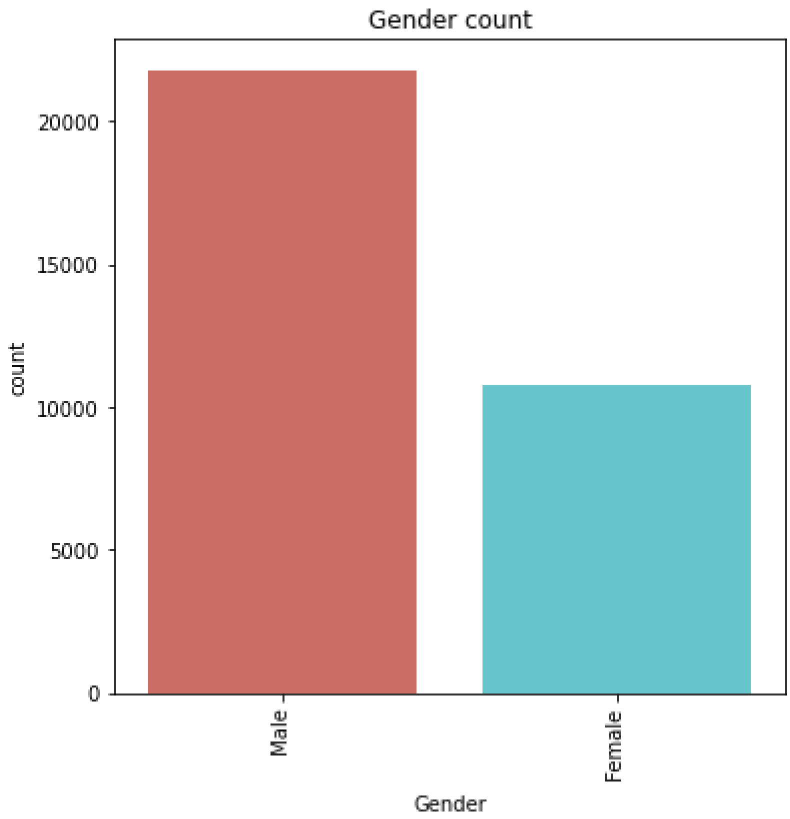
```
salary_pre_data['Gender'].value_counts()
```

Out[267]:

```
 Male      21775
 Female    10762
Name: Gender, dtype: int64
```

In [268]:

```
plt.figure(figsize=(6,6))
sns.countplot(salary_pre_data['Gender'],data=salary_pre_data,palette='hls')
plt.xticks(rotation = 90)
plt.title('Gender count')
plt.show()
```



In [269]:

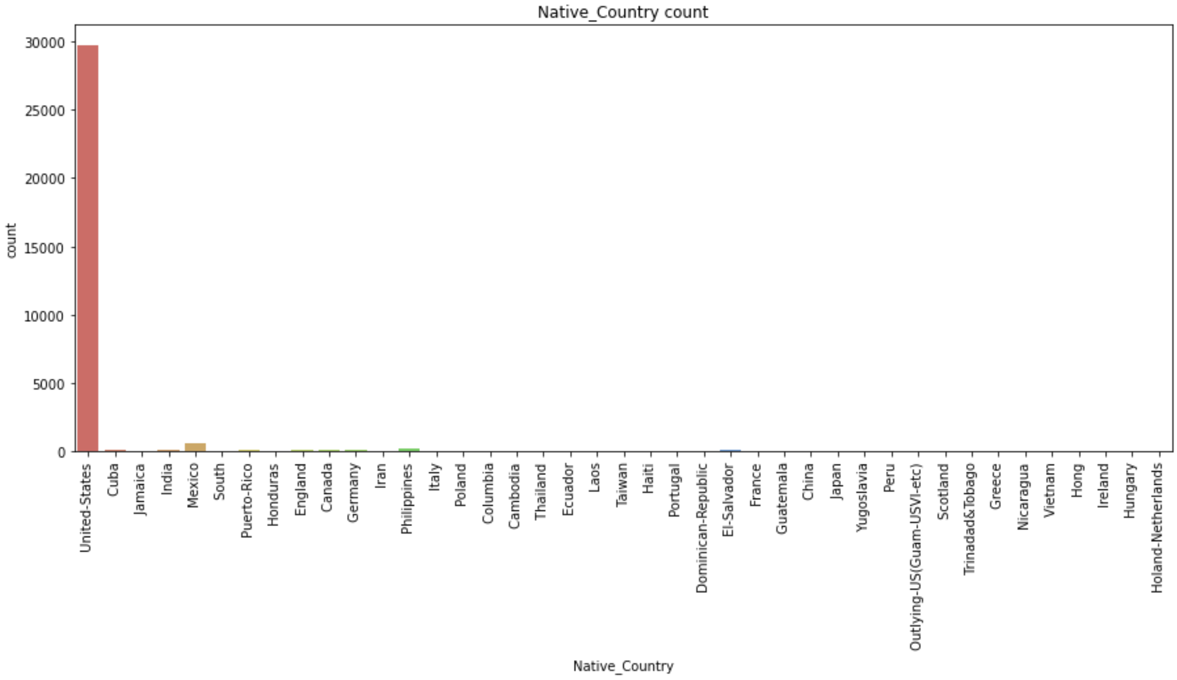
```
salary_pre_data['Native_Country'].value_counts()
```

Out[269]:

```
 United-States                 29735
 Mexico                          639
 Philippines                     198
 Germany                         137
 Canada                          121
 Puerto-Rico                     114
 El-Salvador                     106
 India                           100
 Cuba                             95
 England                          90
 Jamaica                          81
 South                            80
 China                            75
 Italy                            73
 Dominican-Republic               70
 Vietnam                          67
 Japan                            62
 Guatemala                        62
 Poland                           60
 Columbia                         59
 Taiwan                           51
 Haiti                            44
 Iran                             43
 Portugal                         37
 Nicaragua                        34
 Peru                             31
 France                           29
 Greece                           29
 Ecuador                          28
 Ireland                          24
 Hong                             20
 Cambodia                         19
 Trinadad&Tobago                  19
 Laos                             18
 Thailand                         18
 Yugoslavia                       16
 Outlying-US(Guam-USVI-etc)       14
 Honduras                         13
 Hungary                          13
 Scotland                         12
 Holand-Netherlands                1
Name: Native_Country, dtype: int64
```

In [270]:

```
plt.figure(figsize=(15,6))
sns.countplot(salary_pre_data['Native_Country'],data=salary_pre_data,palette='hls')
plt.xticks(rotation = 90)
plt.title('Native_Country count')
plt.show()
```



In [271]:

```
#Due to the high values we decide to drop other country if we not drop the column model wil
#salary_pre_data=salary_pre_data[salary_pre_data['Native_Country'] == 'United-States']
salary_pre_data.drop(columns='Native_Country',inplace=True)
```

In [272]:

```
salary_pre_data.head()
```

Out[272]:

	Age	Employee_Type	Education	Marital_Status	Occupation	Gender	Hours_Per_Week	Sala
0	39	State-gov	Bachelors	other	Adm-clerical	Male	40	<=5(
1	50	Self-emp-not-inc	Bachelors	Married	Exec-managerial	Male	13	<=5(
2	38	Private	HS-grad	other	Handlers-cleaners	Male	40	<=5(
3	53	Private	School Education	Married	Handlers-cleaners	Male	40	<=5(
4	28	Private	Bachelors	Married	Prof-specialty	Female	40	<=5(

In [274]:

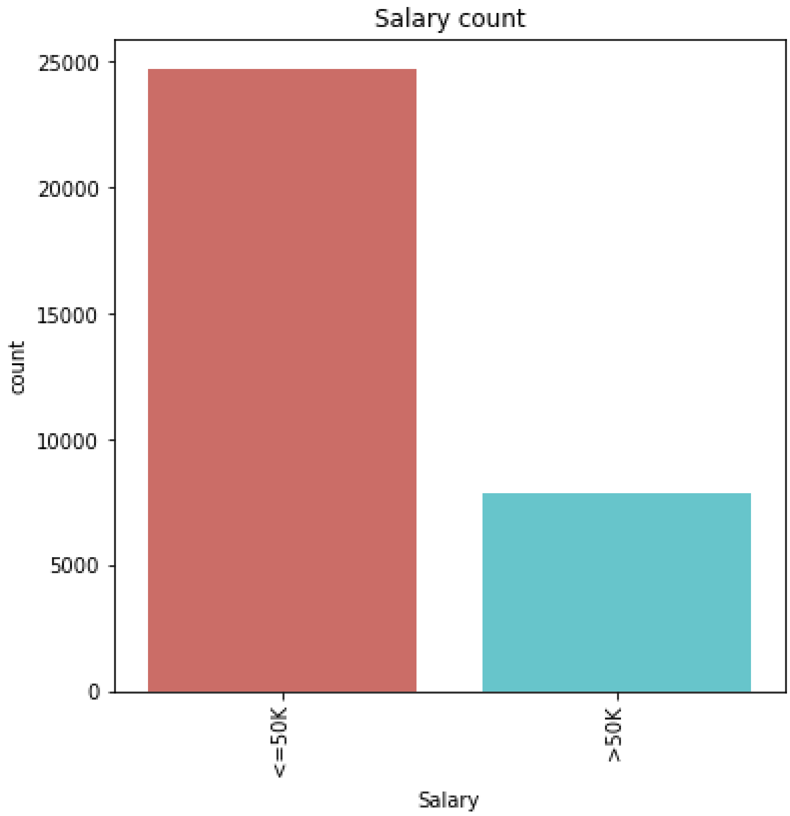
```
salary_pre_data['Salary'].value_counts()
```

Out[274]:

```
 <=50K    24698
 >50K      7839
Name: Salary, dtype: int64
```

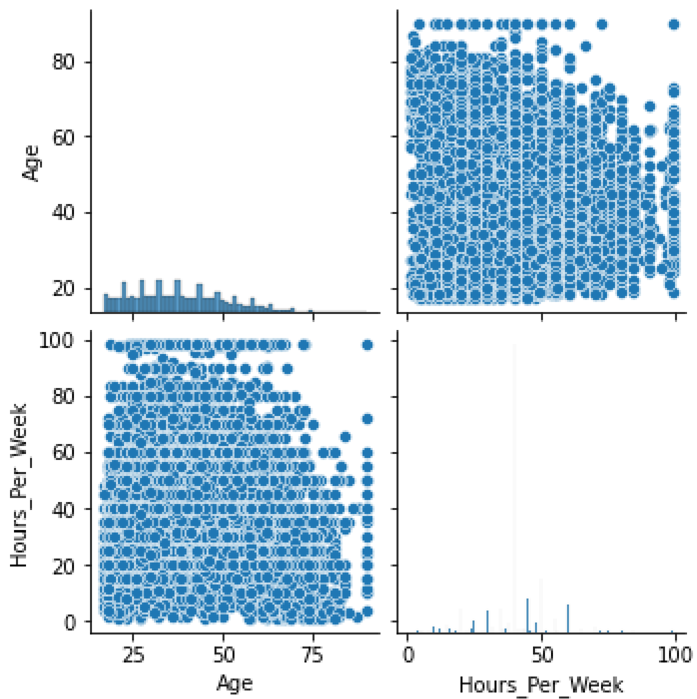
In [275]:

```
plt.figure(figsize=(6,6))
sns.countplot(salary_pre_data['Salary'],data=salary_pre_data,palette='hls')
plt.xticks(rotation = 90)
plt.title('Salary count')
plt.show()
```



In [279]:

```
sns.pairplot(salary_pre_data)
plt.show()
```



In [280]:

```
from sklearn.preprocessing import LabelEncoder
label = LabelEncoder()
salary_pre_data['Education']=label.fit_transform(salary_pre_data['Education'])
salary_pre_data['Marital_Status']=label.fit_transform(salary_pre_data['Marital_Status'])
salary_pre_data['Occupation']=label.fit_transform(salary_pre_data['Occupation'])
salary_pre_data['Gender']=label.fit_transform(salary_pre_data['Gender'])
salary_pre_data['Salary']=label.fit_transform(salary_pre_data['Salary'])
salary_pre_data['Employee_Type']=label.fit_transform(salary_pre_data['Employee_Type'])
salary_pre_data.head()
```

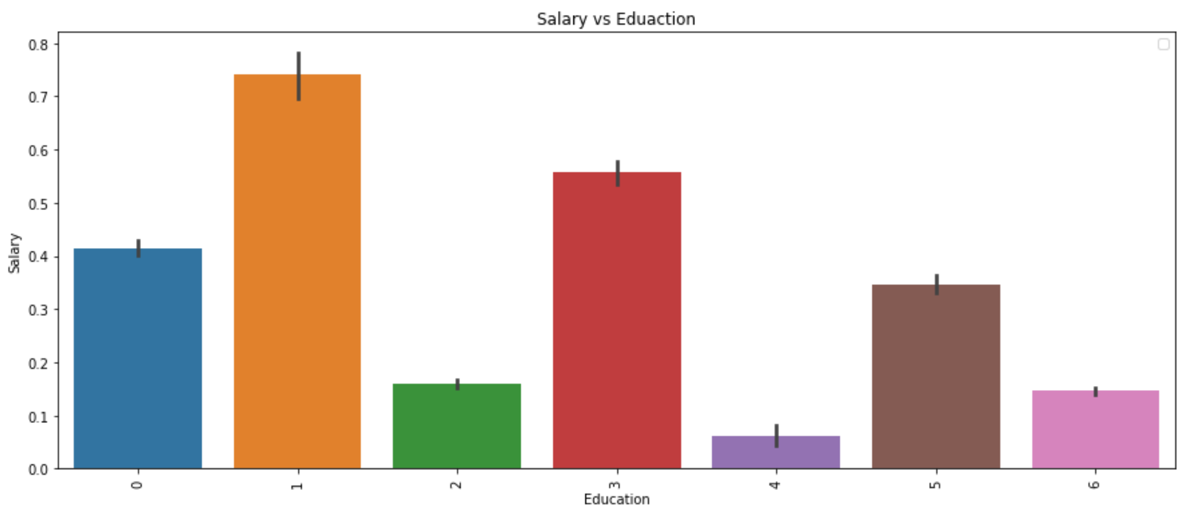
Out[280]:

	Age	Employee_Type	Education	Marital_Status	Occupation	Gender	Hours_Per_Week	Sala
0	39	6	0	1	0	1	40	
1	50	5	0	0	3	1	13	
2	38	3	2	1	5	1	40	
3	53	3	6	0	5	1	40	
4	28	3	0	0	9	0	40	

In [290]:

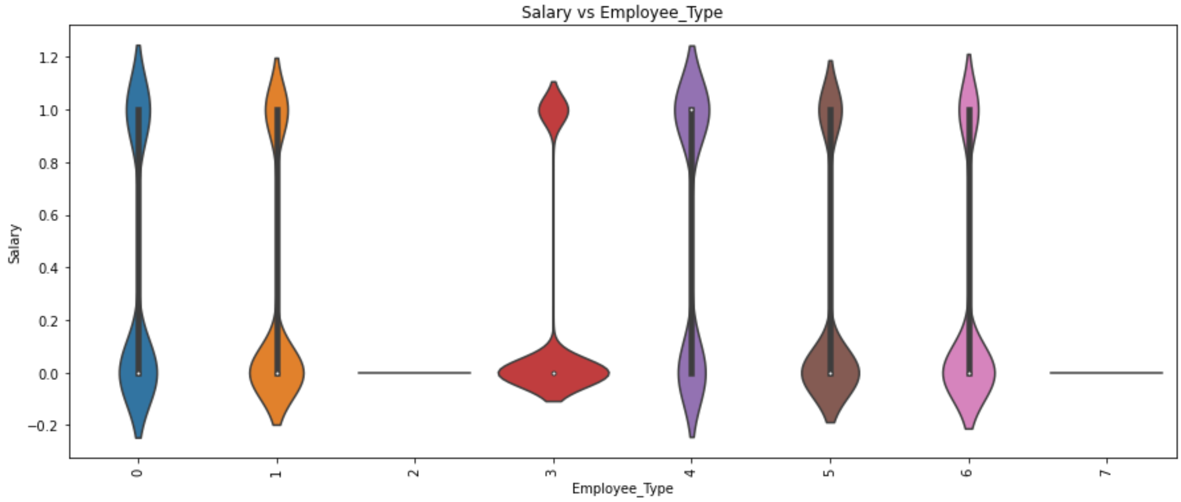
```
#How Salary depent on eduaction
plt.figure(figsize=(15,6))
sns.barplot(x='Education',y='Salary',data=salary_pre_data)
plt.title('Salary vs Eduaction')
plt.xticks(rotation = 90)
plt.legend()
plt.show()
```

No handles with labels found to put in legend.



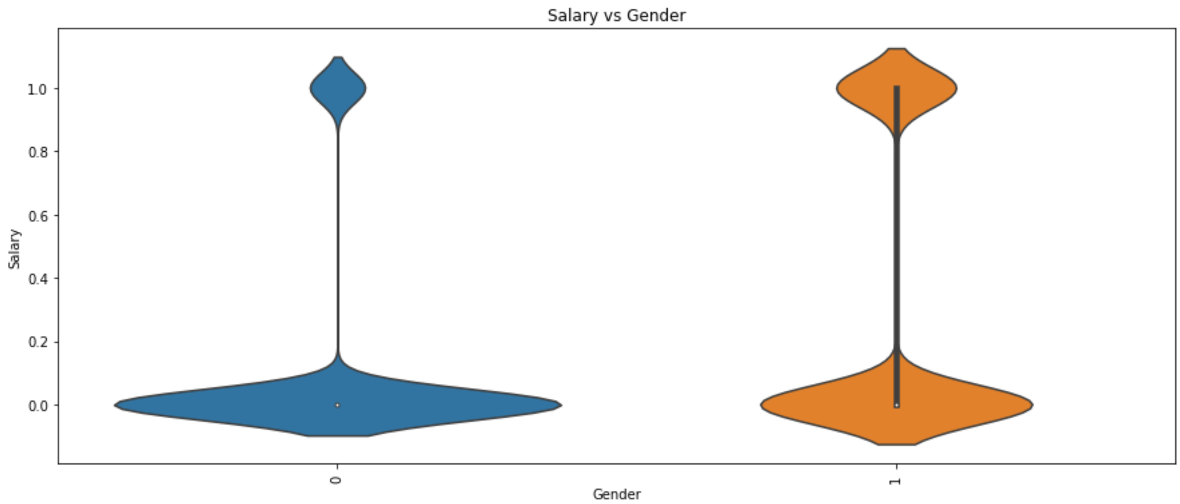
In [291]:

```
plt.figure(figsize=(15,6))
sns.violinplot(x='Employee_Type',y='Salary',data=salary_pre_data)
plt.title('Salary vs Employee_Type')
plt.xticks(rotation = 90)
plt.show()
```



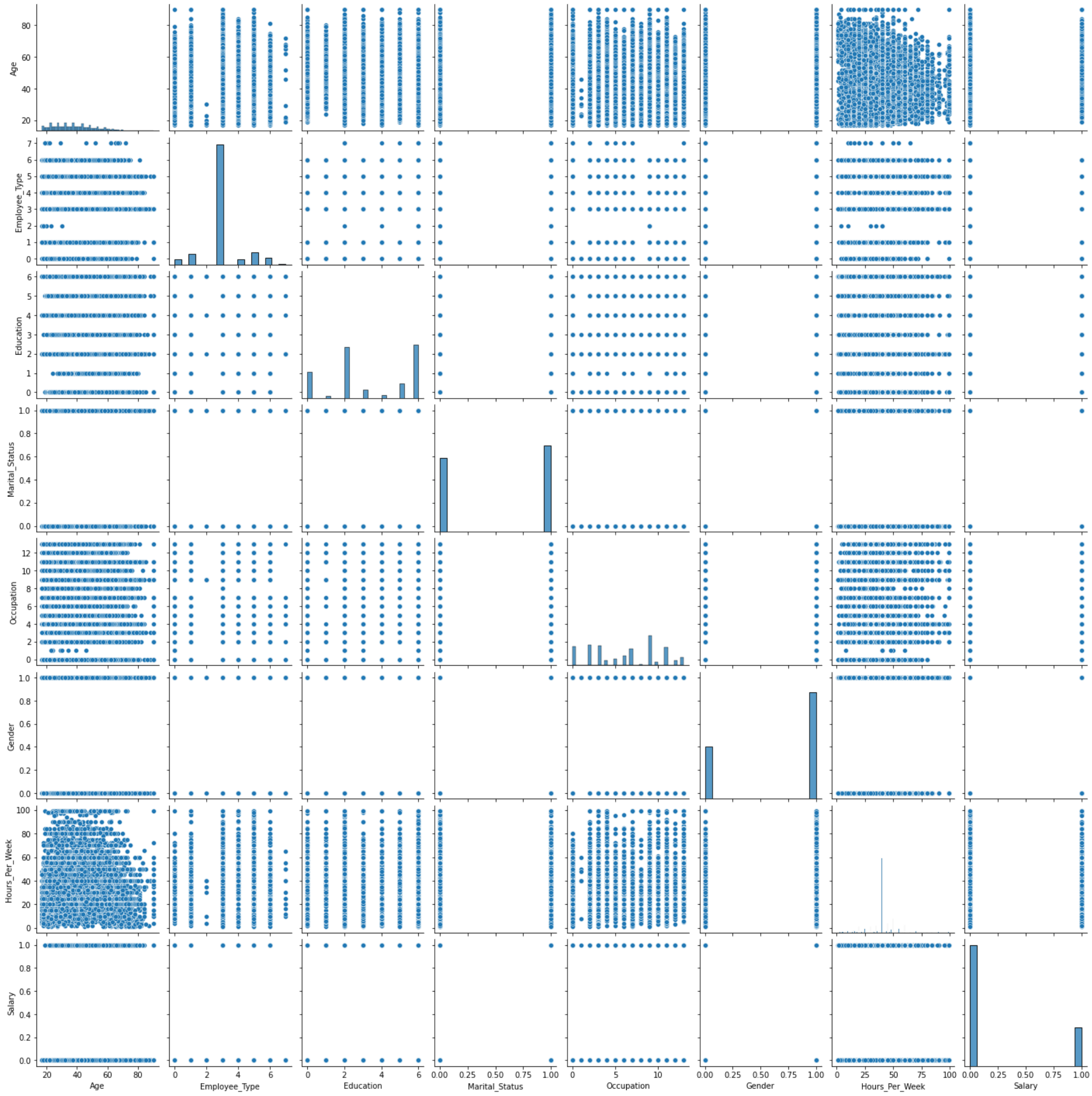
In [292]:

```
plt.figure(figsize=(15,6))
sns.violinplot(x='Gender',y='Salary',data=salary_pre_data)
plt.title('Salary vs Gender')
plt.xticks(rotation = 90)
plt.show()
```



In [293]:

```
sns.pairplot(salary_pre_data,palette='hls')
plt.show()
```

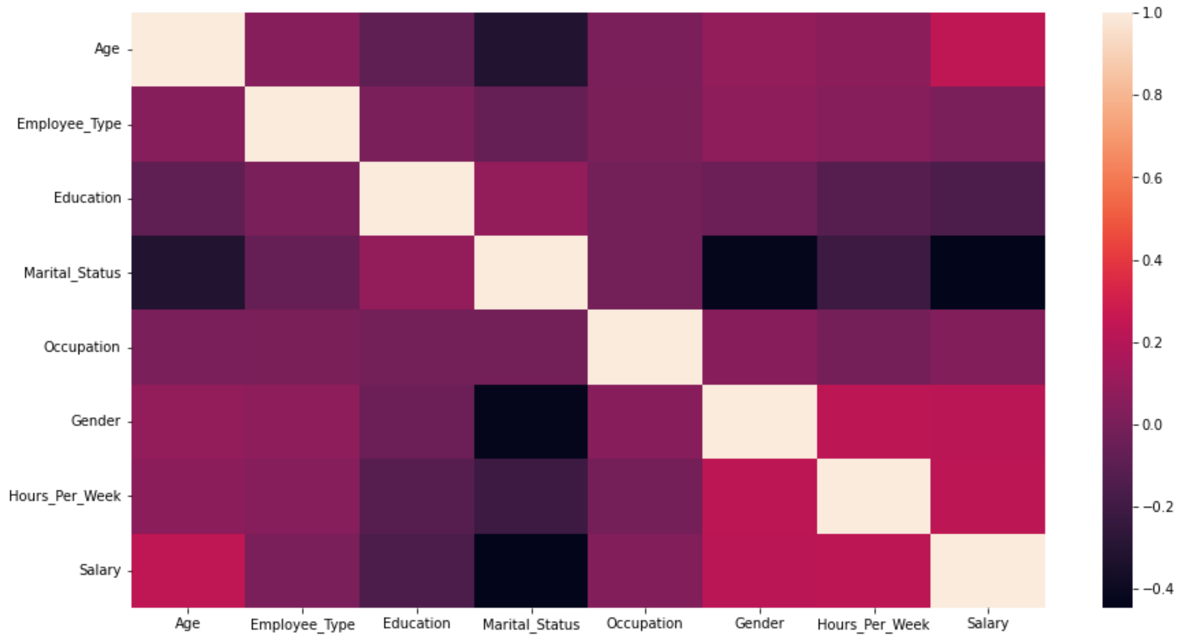


In [294]:

```
plt.figure(figsize=(15,8))
sns.heatmap(salary_pre_data.corr())
```

Out[294]:

```
<AxesSubplot:>
```



In [295]:

```
x = salary_pre_data.iloc[:,:-1].values #independent variable

y = salary_pre_data.iloc[:,-1:].values #dependent variable
```

In [296]:

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(x)
scaled_data = scaler.transform(x)
```

In [297]:

```
x = pd.DataFrame(scaled_data,columns=['Age', 'Employee_Type', 'Education', 'Marital_Status'
x
```

Out[297]:

	Age	Employee_Type	Education	Marital_Status	Occupation	Gender	Hours_Per_
0	0.030390	2.623449	-1.488249	0.924443	-1.545209	0.703020	-0.0
1	0.836973	1.720541	-1.488249	-1.081733	-0.790133	0.703020	-2.2
2	-0.042936	-0.085276	-0.604470	0.924443	-0.286749	0.703020	-0.0
3	1.056950	-0.085276	1.163089	-1.081733	-0.286749	0.703020	-0.0
4	-0.776193	-0.085276	-1.488249	-1.081733	0.720018	-1.422436	-0.0
...	...	...	...	...	...	...	
32532	-0.849519	-0.085276	0.721200	-1.081733	1.475094	-1.422436	-0.1
32533	0.103716	-0.085276	-0.604470	-1.081733	-0.035058	0.703020	-0.0
32534	1.423579	-0.085276	-0.604470	0.924443	-1.545209	-1.422436	-0.0
32535	-1.216148	-0.085276	-0.604470	0.924443	-1.545209	0.703020	-1.6
32536	0.983625	0.817632	-0.604470	-1.081733	-0.790133	-1.422436	-0.0

32537 rows × 7 columns

In [298]:

```
#split data into training and test data
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y,train_size=0.2,random_state=1)
```

Logistic Regression

In [299]:

```
#Here we use logistic Regression Algorithm to trian model
from sklearn.linear_model import LogisticRegression
logi_regg = LogisticRegression()
logi_regg.fit(x_train,y_train)
```

Out[299]:

```
LogisticRegression()
```

In [300]:

```
#predict the test data
y_pred_logi = logi_regg.predict(x_test)
```

In [301]:

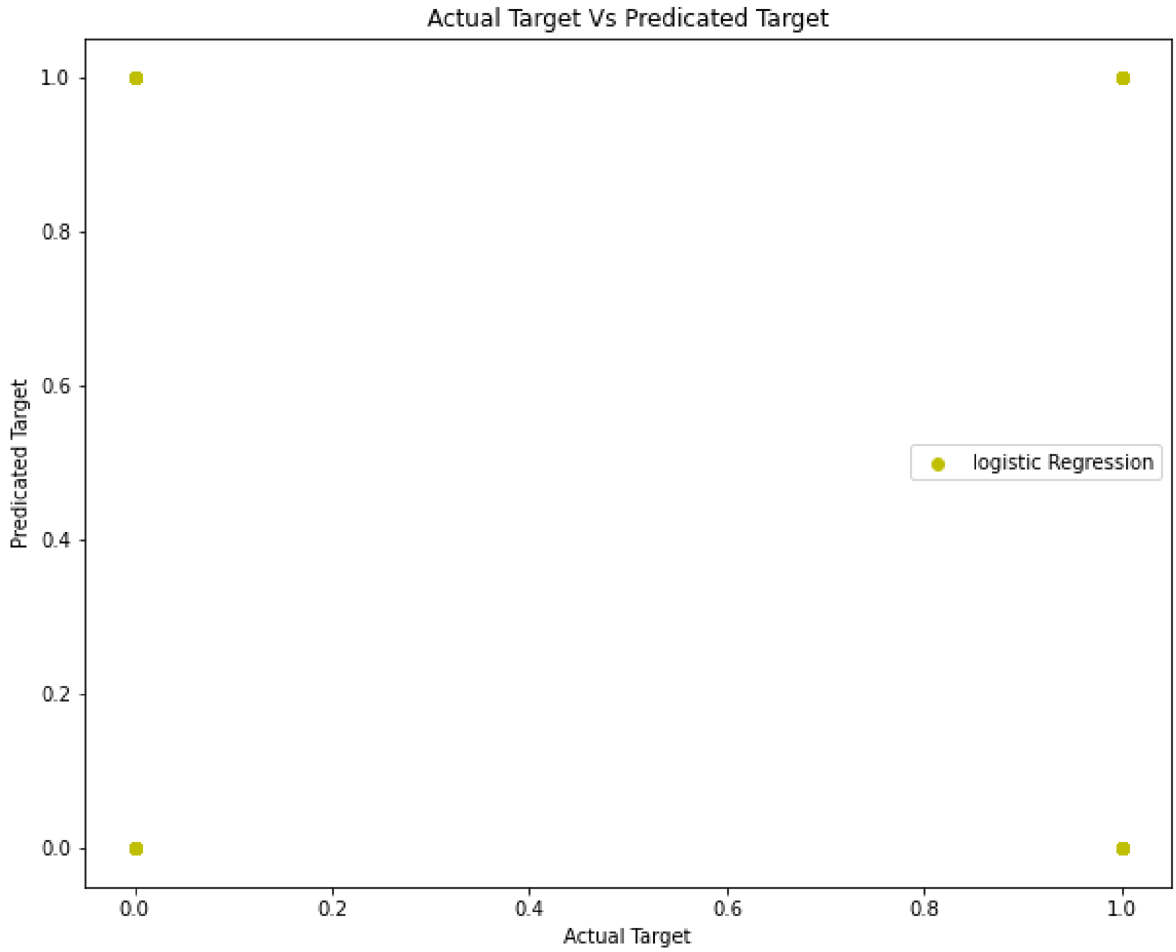
```
#Here we check the accuracy of model with the help of accuracy score and confusion metrix
from sklearn.metrics import accuracy_score,confusion_matrix
score_logi = accuracy_score(y_test,y_pred_logi)
print('Accuracy of model is : ',score_logi)

error_logi = confusion_matrix(y_test,y_pred_logi)
print("Correct and Incorrect input data :'\n'", error_logi)
```

```
Accuracy of model is :  0.7829043411448329
Correct and Incorrect input data :'
' [[17820  1982]
 [ 3669  2559]]
```

In [302]:

```
#visulation of the Acutal Target and Predicated target
plt.figure(figsize=(10,8))
plt.scatter(y_test,y_pred_logi,c='y',label='logistic Regression')
plt.xlabel('Actual Target')
plt.ylabel('Predicated Target')
plt.title('Actual Target Vs Predicated Target')
plt.legend()
plt.show()
```



K-Nearest Neighbours

In [303]:

```
from sklearn.neighbors import KNeighborsClassifier
list1 = []
list2 = []
for i in range(3,50,2):
    knn=KNeighborsClassifier(n_neighbors=i)
    knn.fit(x_train,y_train)
    from sklearn.metrics import accuracy_score
    y_pred = knn.predict(x_test)
    score = accuracy_score(y_test,y_pred)
    list1.append(score)
    list2.append(i)
print(list1)
print(list2)
#print(i)
```

```
[0.788897426046869, 0.7996926623127161, 0.8025739531310027, 0.80476373415290
05, 0.8065693430656934, 0.8071840184402612, 0.8071840184402612, 0.8080291970
80292, 0.8067998463311563, 0.8072608528620823, 0.806607760276604, 0.80610833
65347675, 0.806607760276604, 0.8054168267383788, 0.8049558202074529, 0.80345
75489819439, 0.8042258932001537, 0.8045332308874376, 0.8049558202074529, 0.8
034191317710334, 0.8043027276219746, 0.8042643104110642, 0.8044179792547062,
0.8037648866692279]
[3, 5, 7, 9, 11, 13, 15, 17, 19, 21, 23, 25, 27, 29, 31, 33, 35, 37, 39, 41,
43, 45, 47, 49]
```

In [304]:

```
df = pd.DataFrame(list1,columns=['score'])
df['k_values'] = list2
df
```

Out[304]:

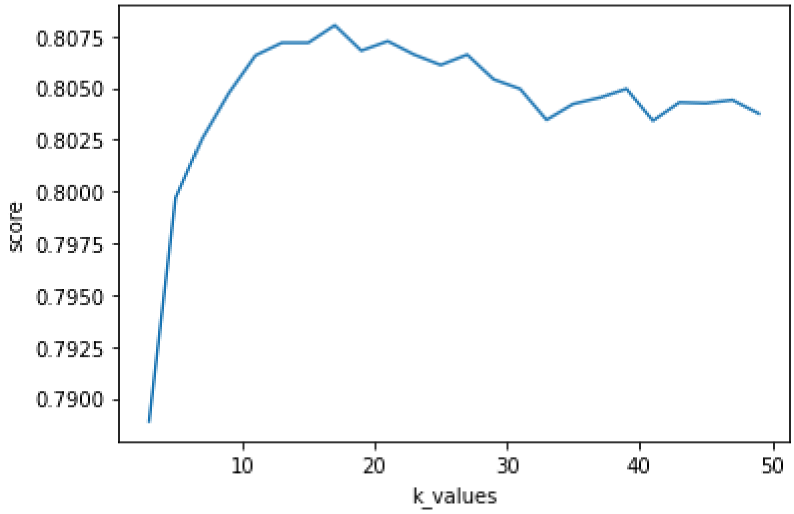
	score	k_values
0	0.788897	3
1	0.799693	5
2	0.802574	7
3	0.804764	9
4	0.806569	11
5	0.807184	13
6	0.807184	15
7	0.808029	17
8	0.806800	19
9	0.807261	21
10	0.806608	23
11	0.806108	25
12	0.806608	27
13	0.805417	29
14	0.804956	31
15	0.803458	33
16	0.804226	35
17	0.804533	37
18	0.804956	39
19	0.803419	41
20	0.804303	43
21	0.804264	45
22	0.804418	47
23	0.803765	49

In [305]:

```
#here we plot the line graph
sns.lineplot(df.k_values,df.score)
#df.plot(x = 'k_values',y='score',kind='line')
```

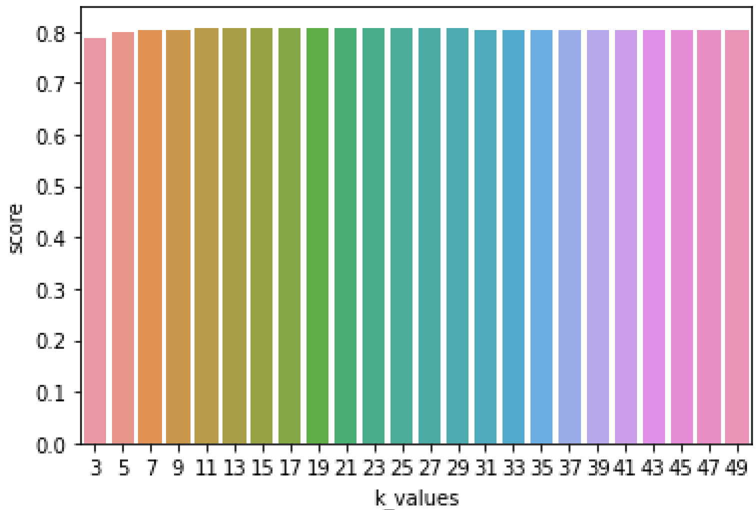
Out[305]:

```
<AxesSubplot:xlabel='k_values', ylabel='score'>
```



In [306]:

```
#df.plot(x = 'mse',y='k_values',kind='bar')
sns.barplot(df.k_values,df.score)
plt.show()
```



In [307]:

```
knn = KNeighborsClassifier(n_neighbors=17)
knn.fit(x_train,y_train)
knn
```

Out[307]:

```
KNeighborsClassifier(n_neighbors=17)
```

In [308]:

```
y_pred_knn = knn.predict(x_test)
```

In [309]:

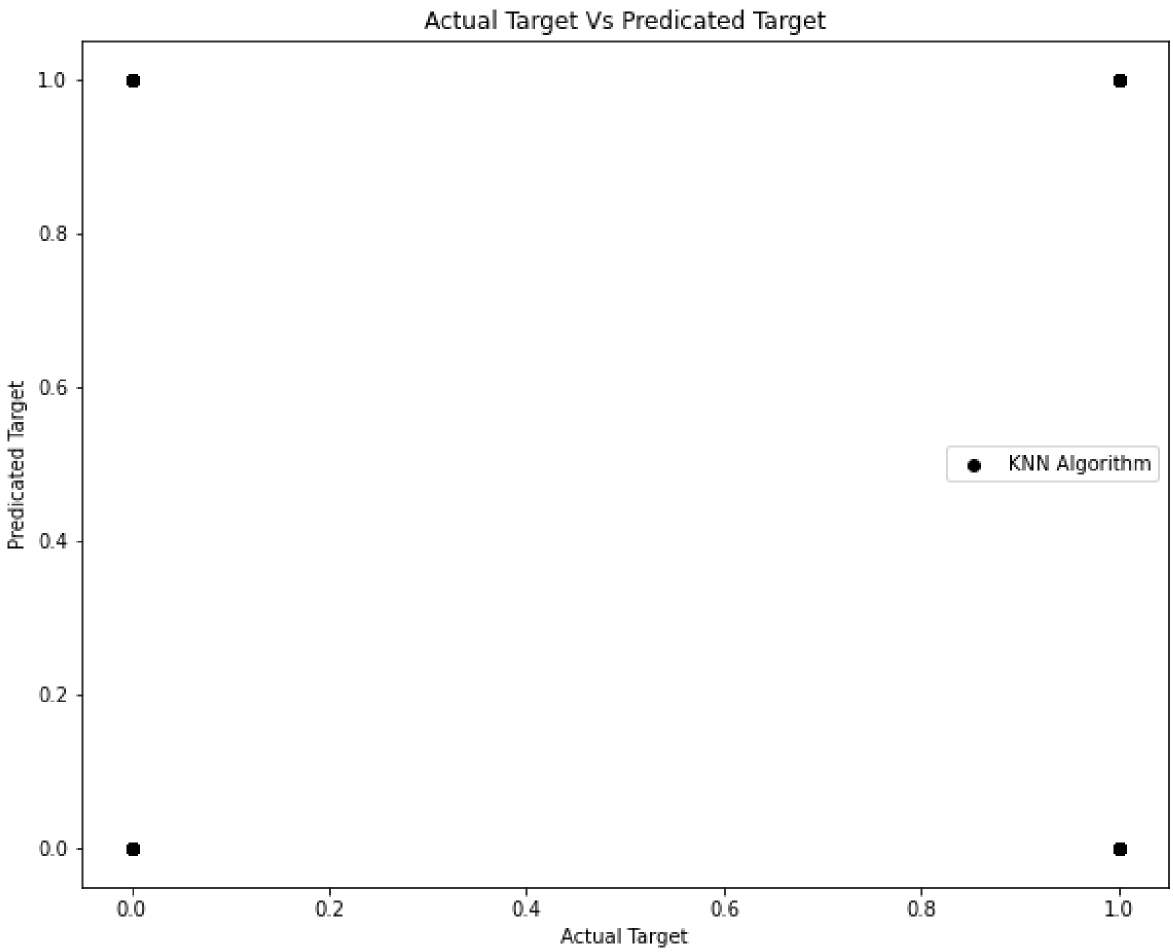
```
#Here we check the accuracy of model with the help of accuracy score and confusion metrix
from sklearn.metrics import accuracy_score,confusion_matrix
score_knn = accuracy_score(y_test,y_pred_knn)
print('Accuracy of model is : ',score_knn)

error_knn = confusion_matrix(y_test,y_pred_knn)
print("Correct and Incorrect input data :'\n'", error_knn)
```

```
Accuracy of model is :  0.808029197080292
Correct and Incorrect input data :'
' [[17580  2222]
 [ 2775  3453]]
```

In [310]:

```
#visulation of the Acutal Target and Predicated target
plt.figure(figsize=(10,8))
plt.scatter(y_test,y_pred_knn,c='k',label='KNN Algorithm')
plt.xlabel('Actual Target')
plt.ylabel('Predicated Target')
plt.title('Actual Target Vs Predicated Target')
plt.legend()
plt.show()
```



Support Vector Machine Algorithm

In [311]:

```
from sklearn import svm
#from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
kernel_name = ['linear', 'poly', 'rbf','sigmoid'] #{'linear', 'poly', 'rbf', 'sigmoid', 'pr
score_store = []
for i in kernel_name:
    cv_classification = svm.SVC(kernel=i)#SVC = support vector classifier
    cv_classification.fit(x_train,y_train)
    y_pred = cv_classification.predict(x_test)
    score = accuracy_score(y_test,y_pred)
    score_store.append(score)
score_store
```

Out[311]:

```
[0.7872839031886285, 0.8026123703419131, 0.806377257011141, 0.71940069150979
64]
```

In [312]:

```
df1 = pd.DataFrame(score_store,columns=['score'])
df1['kernal'] = kernel_name
df1
```

Out[312]:

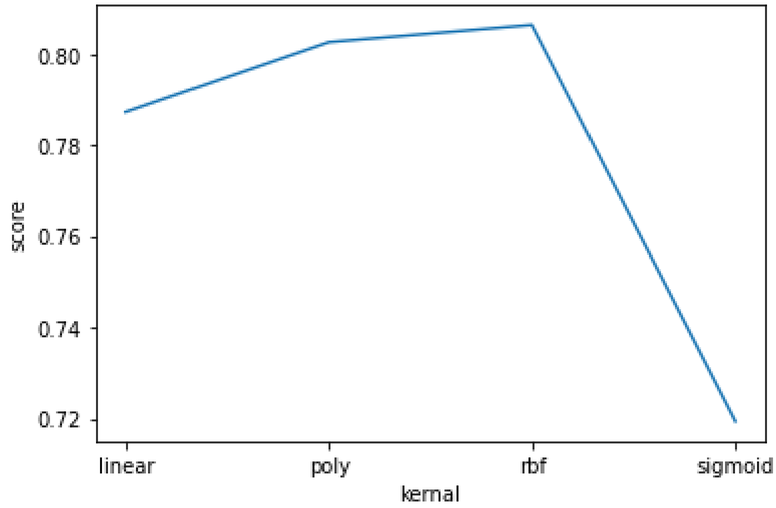
	score	kernal
0	0.787284	linear
1	0.802612	poly
2	0.806377	rbf
3	0.719401	sigmoid

In [313]:

```
#here we plot the line graph
sns.lineplot(df1.kernal,df1.score)
#df1.plot(x = 'kernal',y='score',kind='line')
```

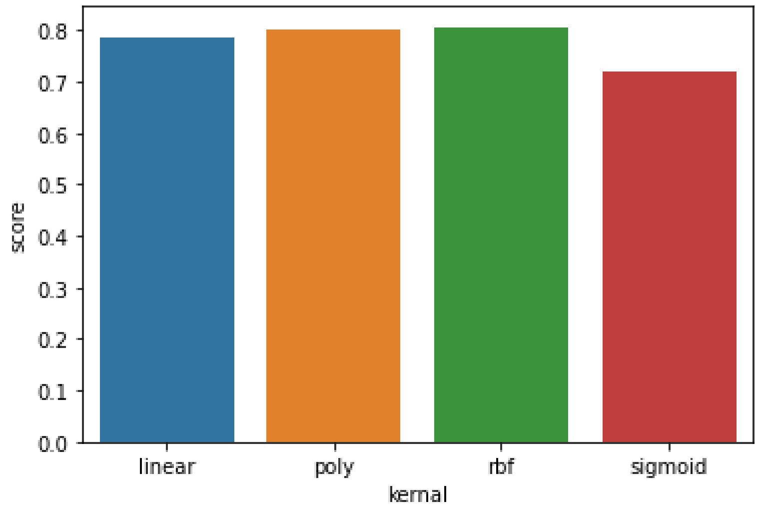
Out[313]:

```
<AxesSubplot:xlabel='kernal', ylabel='score'>
```



In [319]:

```
#df1.plot(x = 'score',y='k_values',kind='bar')
sns.barplot(df1.kernal,df1.score)
plt.show()
```



In [320]:

```
#Used support vector machine
cv_classification = svm.SVC(kernel='rbf')    #SVC = support vector classifier
cv_classification.fit(x_train,y_train)
```

Out[320]:

```
SVC()
```

In [321]:

```
y_pred_svm = cv_classification.predict(x_test)
```

In [322]:

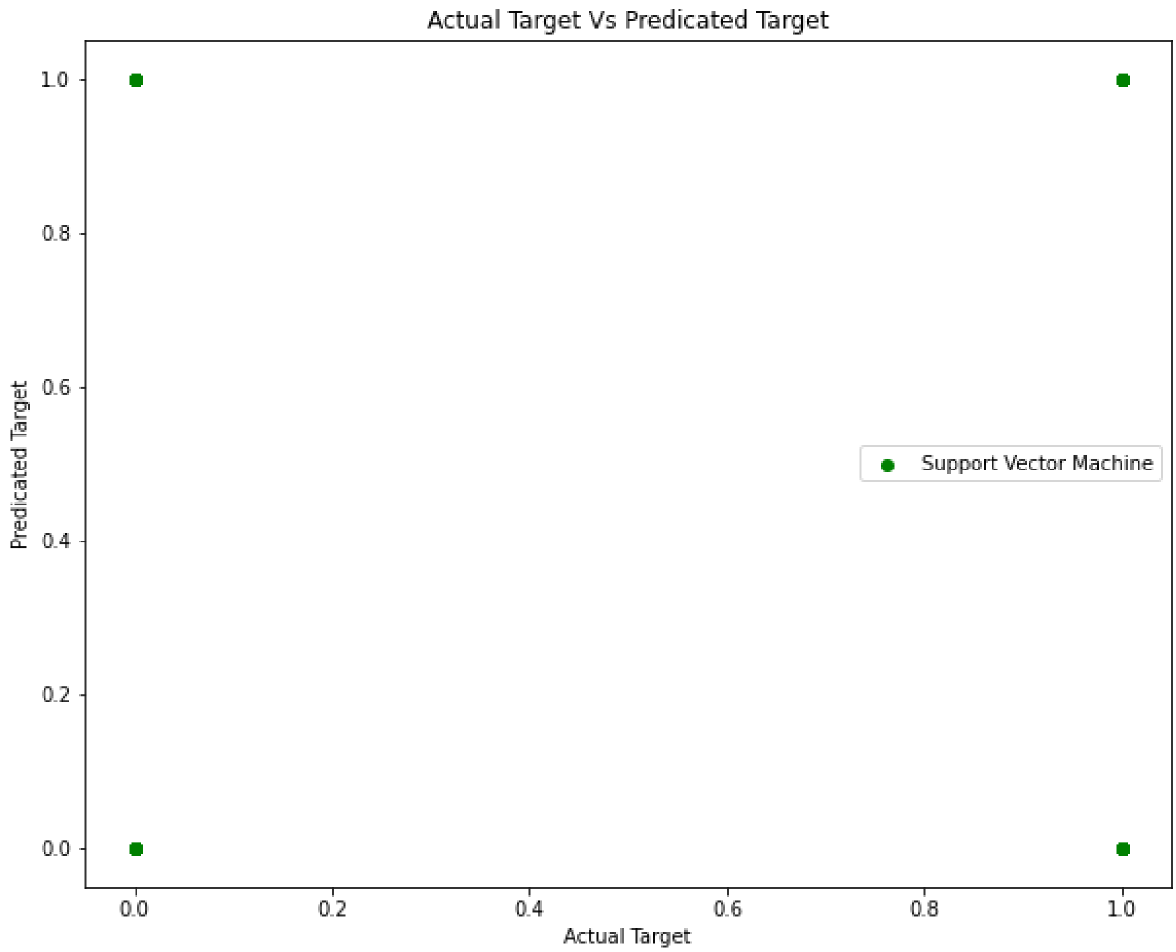
```
#Here we check the accuracy of model with the help of accuracy score and confusion metrix
from sklearn.metrics import accuracy_score,confusion_matrix
score_svm = accuracy_score(y_test,y_pred_svm)
print('Accuracy of model is : ',score_svm)

error_svm = confusion_matrix(y_test,y_pred_svm)
print("Correct and Incorrect input data :'\n'", error_svm)
```

```
Accuracy of model is :  0.806377257011141
Correct and Incorrect input data :'
' [[17959  1843]
 [ 3197  3031]]
```

In [323]:

```
#visulation of the Acutal Target and Predicated target
plt.figure(figsize=(10,8))
plt.scatter(y_test,y_pred_svm,c='g',label='Support Vector Machine')
plt.xlabel('Actual Target')
plt.ylabel('Predicated Target')
plt.title('Actual Target Vs Predicated Target')
plt.legend()
plt.show()
```



Decision Tree Classification Algorithm

In [324]:

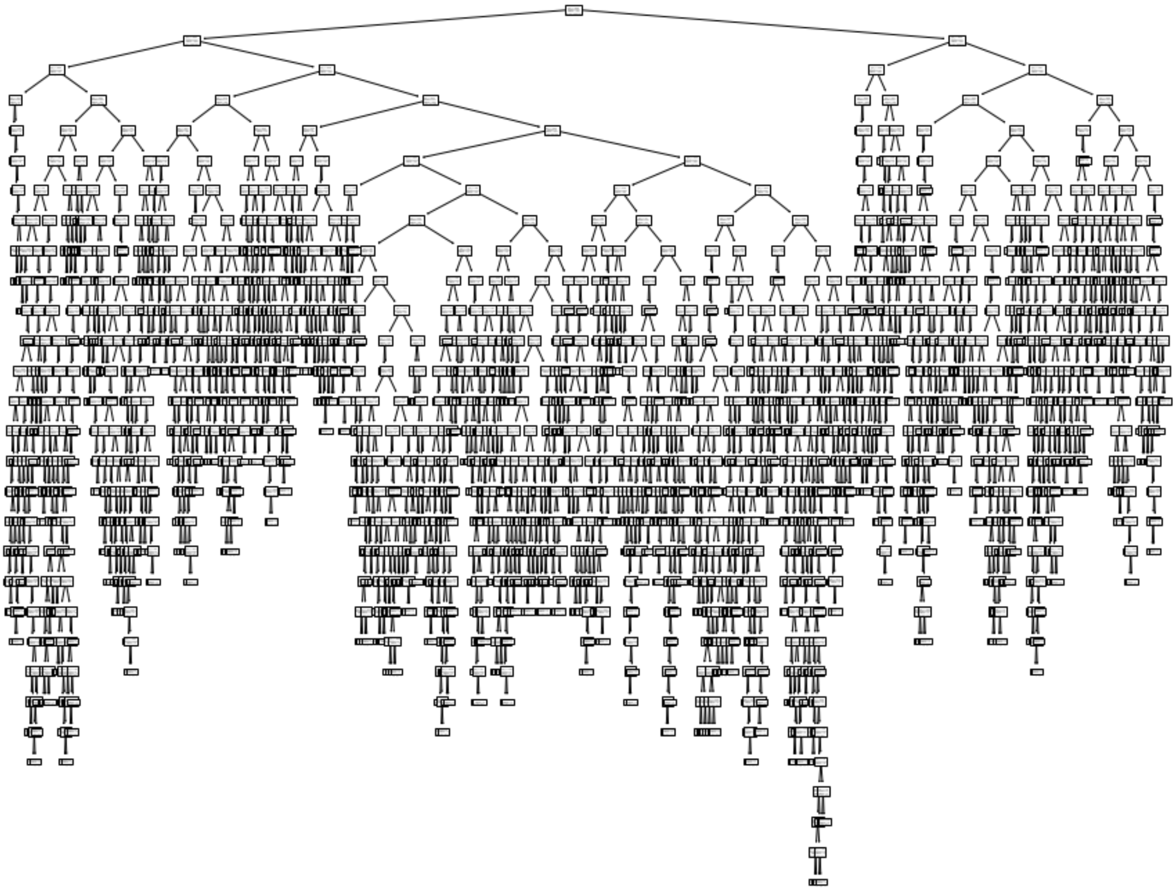
```
from sklearn.tree import DecisionTreeClassifier
dt_classifier = DecisionTreeClassifier(criterion='entropy') # entropy = information gain
dt_classifier.fit(x_train,y_train)
```

Out[324]:

```
DecisionTreeClassifier(criterion='entropy')
```

In [325]:

```
from sklearn import tree
fig = plt.figure(figsize=(15,12))
x=tree.plot_tree(dt_classifier)
```



In [326]:

```
y_pred_dt = dt_classifier.predict(x_test)
```

In [327]:

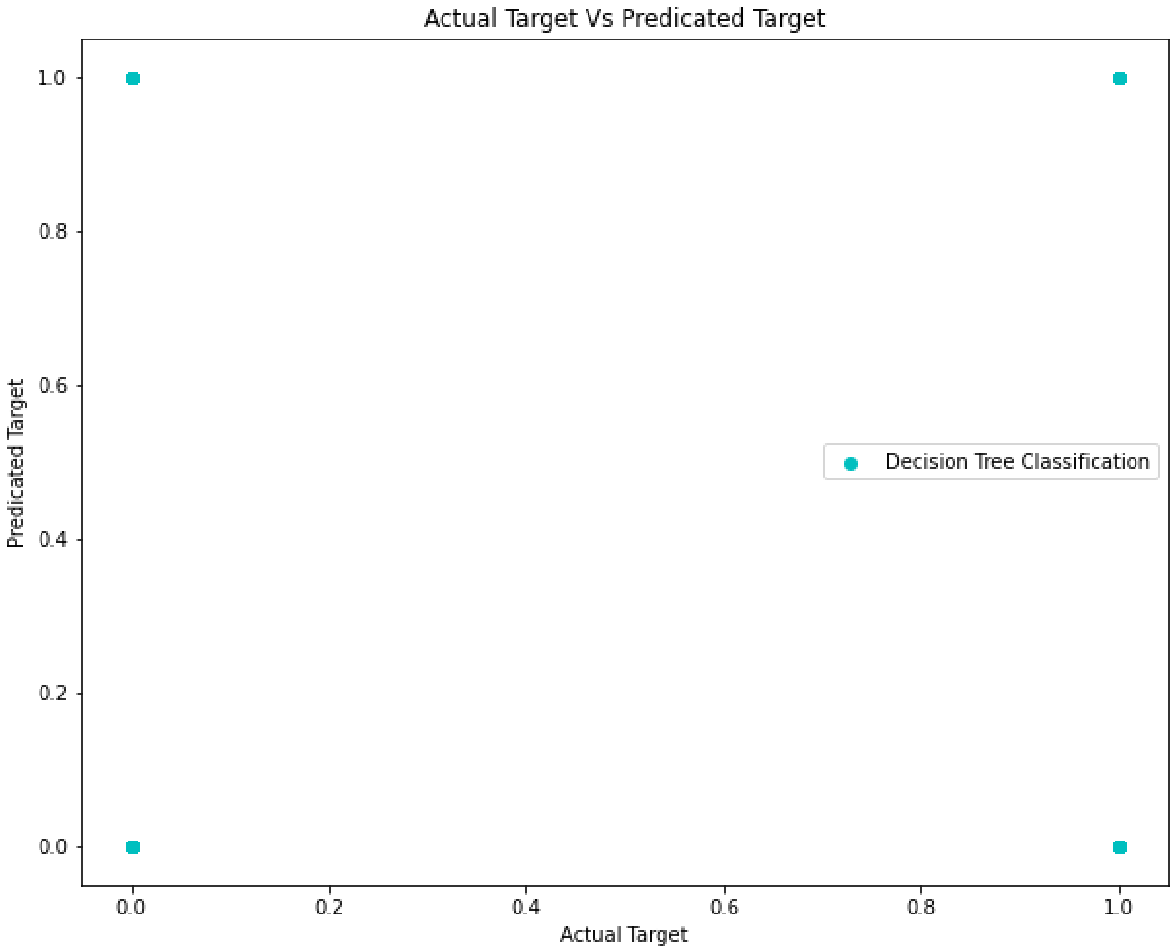
```
#Here we check the accuracy of model with the help of accuracy score and confusion metrix
from sklearn.metrics import accuracy_score,confusion_matrix
score_dt = accuracy_score(y_test,y_pred_dt)
print('Accuracy of model is : ',score_dt)

error_dt = confusion_matrix(y_test,y_pred_dt)
print("Correct and Incorrect input data :'\n'", error_dt)
```

```
Accuracy of model is :  0.7709950057625816
Correct and Incorrect input data :'
' [[16738  3064]
 [ 2897  3331]]
```

In [328]:

```
#visulation of the Acutal Target and Predicated target
plt.figure(figsize=(10,8))
plt.scatter(y_test,y_pred_dt,c='c',label='Decision Tree Classification')
plt.xlabel('Actual Target')
plt.ylabel('Predicated Target')
plt.title('Actual Target Vs Predicated Target')
plt.legend()
plt.show()
```



Navie Bayer Classification Algorithm

In [329]:

```
from sklearn.naive_bayes import GaussianNB
NBCA = GaussianNB()
NBCA.fit(x_train,y_train)
```

Out[329]:

```
GaussianNB()
```

In [330]:

```
y_pred_nb = NBCA.predict(x_test)
```

In [331]:

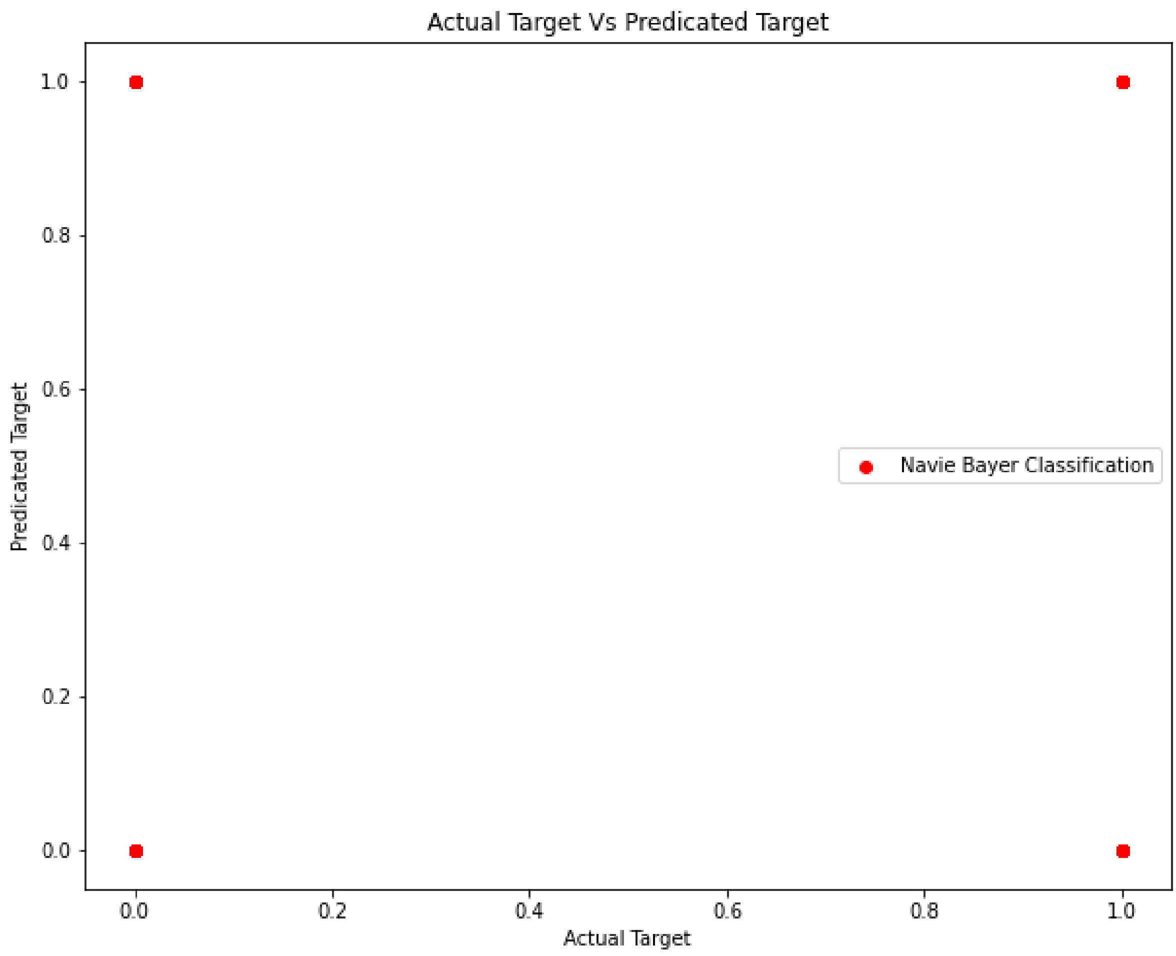
```
#Here we check the accuracy of model with the help of accuracy score and confusion metrix
from sklearn.metrics import accuracy_score,confusion_matrix
score_nb = accuracy_score(y_test,y_pred_nb)
print('Accuracy of model is : ',score_nb)

error_nb = confusion_matrix(y_test,y_pred_nb)
print("Correct and Incorrect input data :'\n'", error_nb)
```

```
Accuracy of model is :  0.7595850941221667
Correct and Incorrect input data :'
' [[15343  4459]
 [ 1799  4429]]
```

In [332]:

```
#visulation of the Acutal Target and Predicated target
plt.figure(figsize=(10,8))
plt.scatter(y_test,y_pred_nb,c='r',label='Navie Bayer Classification')
plt.xlabel('Actual Target')
plt.ylabel('Predicated Target')
plt.title('Actual Target Vs Predicated Target')
plt.legend()
plt.show()
```



Random Forest Classification Algorithm

In [333]:

```
from sklearn.ensemble import RandomForestClassifier
RFAClass = RandomForestClassifier(n_estimators=50) #n_estimators less error maximum and mor
RFAClass.fit(x_train,y_train)
RFAClass.fit(x_train,y_train)
```

Out[333]:

```
RandomForestClassifier(n_estimators=50)
```

In [334]:

```
y_pred_rf = RFAClass.predict(x_test)
```

In [335]:

```
#Here we check the accuracy of model with the help of accuracy score and confusion metrix
from sklearn.metrics import accuracy_score,confusion_matrix
score_rf = accuracy_score(y_test,y_pred_rf)
print('Accuracy of model is : ',score_rf)

error_rf = confusion_matrix(y_test,y_pred_rf)
print("Correct and Incorrect input data :'\n'", error_rf)
```

```
Accuracy of model is :  0.8066845946984249
Correct and Incorrect input data :'
' [[17554  2248]
 [ 2784  3444]]
```

In [336]:

```
#visulation of the Acutal Target and Predicated target
plt.figure(figsize=(10,8))
plt.scatter(y_test,y_pred_rf,c='b',label='Random Forest Classification')
plt.xlabel('Actual Target')
plt.ylabel('Predicated Target')
plt.title('Actual Target Vs Predicated Target')
plt.legend()
plt.show()
```

XGBOOST Classifier

In [338]:

```
from xgboost import XGBClassifier
xgb = XGBClassifier() #n_estimators less error maximum and more error less
xgb.fit(x_train,y_train)
xgb.fit(x_train,y_train)
```

Out[338]:

```
XGBClassifier(base_score=0.5, booster='gbtree', callbacks=None,
              colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
              early_stopping_rounds=None, enable_categorical=False,
              eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwise',
              importance_type=None, interaction_constraints='',
              learning_rate=0.300000012, max_bin=256, max_cat_to_onehot=4,
              max_delta_step=0, max_depth=6, max_leaves=0, min_child_weight=
1,
              missing=nan, monotone_constraints='()', n_estimators=100,
              n_jobs=0, num_parallel_tree=1, predictor='auto', random_state=
0,
              reg_alpha=0, reg_lambda=1, ...)
```

In [339]:

```
y_pred_xgb = xgb.predict(x_test)
```

In [340]:

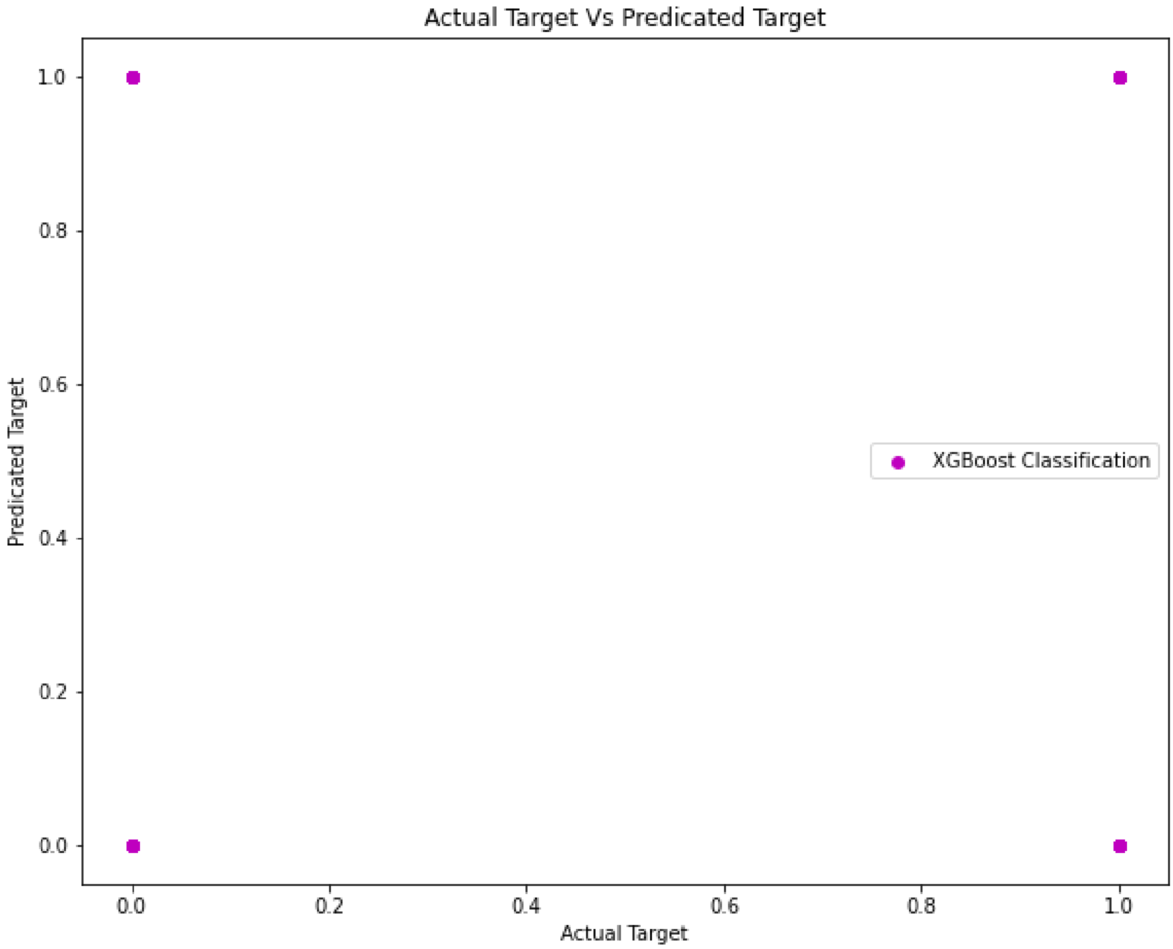
```
#Here we check the accuracy of model with the help of accuracy score and confusion metrix
from sklearn.metrics import accuracy_score,confusion_matrix
score_xgb= accuracy_score(y_test,y_pred_xgb)
print('Accuracy of model is : ',score_xgb)

error_xgb= confusion_matrix(y_test,y_pred_xgb)
print("Correct and Incorrect input data :'\n'", error_xgb)
```

```
Accuracy of model is :  0.8230503265462927
Correct and Incorrect input data :'
' [[17718  2084]
 [ 2522  3706]]
```

In [341]:

```
#visulation of the Acutal Target and Predicated target
plt.figure(figsize=(10,8))
plt.scatter(y_test,y_pred_xgb,c='m',label='XGBoost Classification')
plt.xlabel('Actual Target')
plt.ylabel('Predicated Target')
plt.title('Actual Target Vs Predicated Target')
plt.legend()
plt.show()
```



All Classification Type algorithm result

In [342]:

```
#Here we check the accuracy of model with the help of accuracy score and confusion metrix

print('Logistic Regression')
print('Accuracy of model is : ',score_logi)
print("Correct and Incorrect input data :'\n'", error_logi)


print('\n KNN Classification')
print('Accuracy of model is : ',score_knn)
print("Correct and Incorrect input data :'\n'", error_knn)

print('\n Support Vector Machine classification Algorithm')
print('Accuracy of model is : ',score_svm)
print("Correct and Incorrect input data :'\n'", error_svm)

print('\n Decision Tree Classifcation Algorithm')
print('Accuracy of model is : ',score_dt)
print("Correct and Incorrect input data :'\n'", error_dt)



print('\n Navie Bayes Classification Algorithms')
print('Accuracy of model is : ',score_nb)
print("Correct and Incorrect input data :'\n'", error_nb)


print('\n Random Forest classification Algorithm')
print('Accuracy of model is : ',score_rf)
print("Correct and Incorrect input data :'\n'", error_rf)


print('\n XGBoost Classification')
print('Accuracy of model is : ',score_xgb)
print("Correct and Incorrect input data :'\n'", error_xgb)
```

```
 [ 2897  3331]]

 Navie Bayes Classification Algorithms
Accuracy of model is :  0.7595850941221667
Correct and Incorrect input data :'
' [[15343  4459]
 [ 1799  4429]]

 Random Forest classification Algorithm
Accuracy of model is :  0.8066845946984249
Correct and Incorrect input data :'
' [[17554  2248]
 [ 2784  3444]]

 XGBoost Classification
Accuracy of model is :  0.8230503265462927
Correct and Incorrect input data :'
' [[17718  2084]
 [ 2522  3706]]
```

In [343]:

```
Algorithm = ['Logistic Regression','K-NN','Support VM','Decision Tree','Navie Bayer','Rando
score = [score_logi,score_knn,score_svm,score_dt,score_nb,score_rf,score_xgb]
df_plot = pd.DataFrame(Algorithm,columns=['Algorithm_Name'])
df_plot['Accuracy_Score']=score
df_plot
```

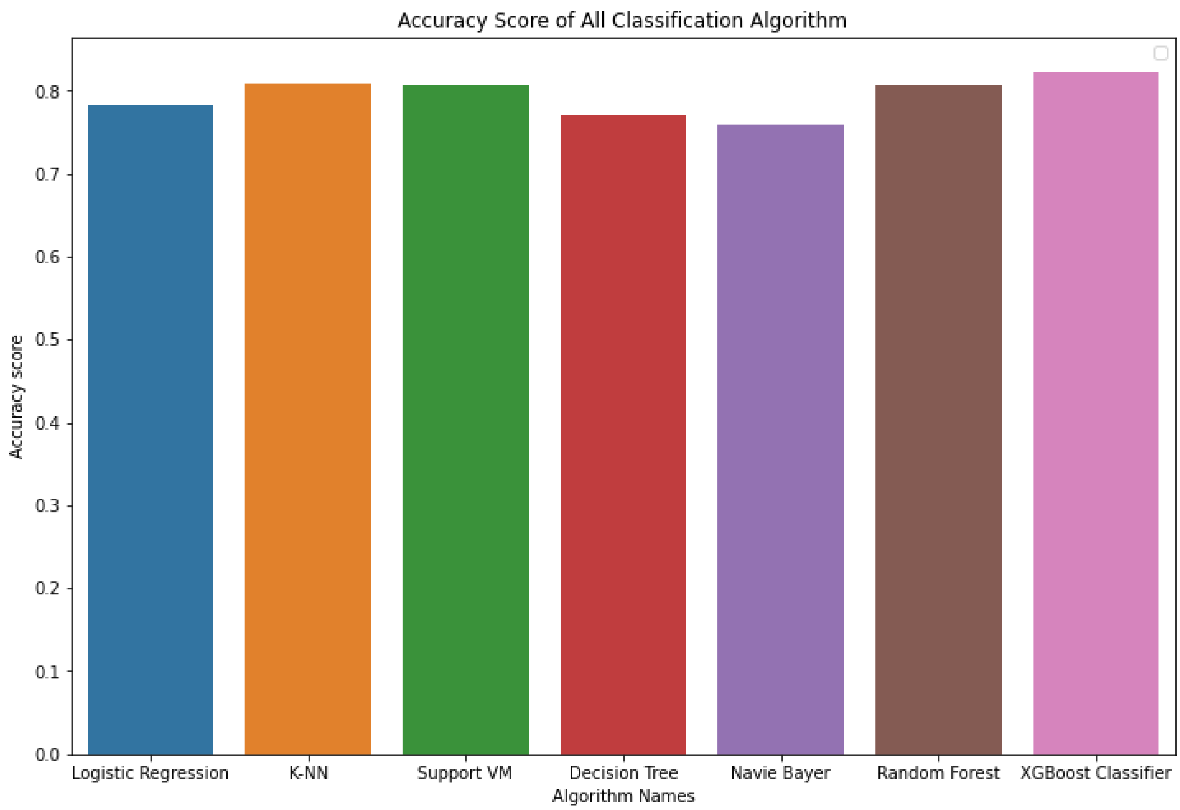
Out[343]:

	Algorithm_Name	Accuracy_Score
0	Logistic Regression	0.782904
1	K-NN	0.808029
2	Support VM	0.806377
3	Decision Tree	0.770995
4	Navie Bayer	0.759585
5	Random Forest	0.806685
6	XGBoost Classifier	0.823050

In [344]:

```
plt.figure(figsize=(12,8))
sns.barplot(df_plot.Algorithm_Name,df_plot.Accuracy_Score)
plt.xlabel('Algorithm Names')
plt.ylabel('Accuracy score')
plt.title('Accuracy Score of All Classification Algorithm')
plt.legend()
plt.show()
```

```
No handles with labels found to put in legend.
```

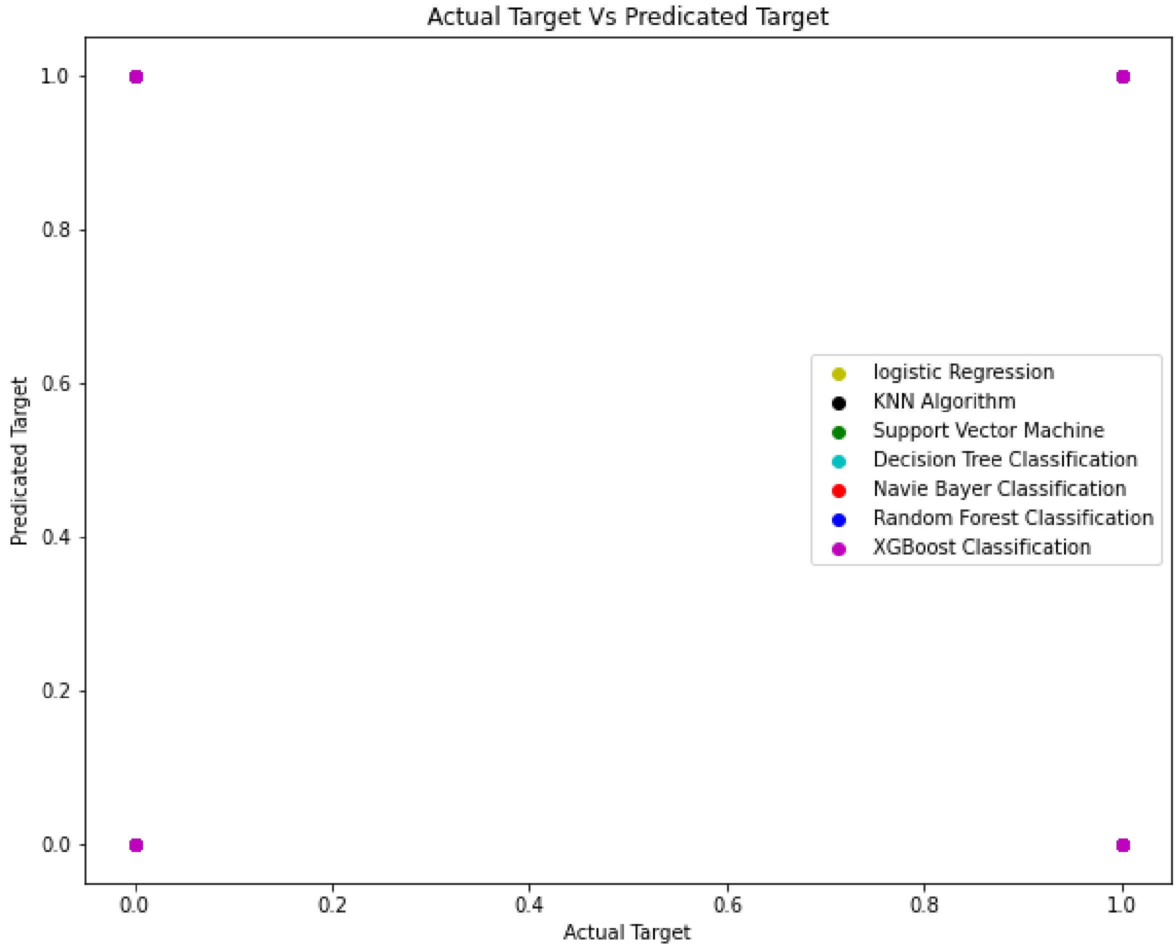


conclusion :

```
- see above plot XGBoost Classifier gives more accuracy to our model
- for salary prediction XGBoost Classifier Algorithm is Efficient.
- XGBoost Classifier Accuracy is 82.30%
```

In [345]:

```
#visulation of the Acutal Target and Predicated target
plt.figure(figsize=(10,8))
plt.scatter(y_test,y_pred_logi,c='y',label='logistic Regression')
plt.scatter(y_test,y_pred_knn,c='k',label='KNN Algorithm')
plt.scatter(y_test,y_pred_svm,c='g',label='Support Vector Machine')
plt.scatter(y_test,y_pred_dt,c='c',label='Decision Tree Classification')
plt.scatter(y_test,y_pred_nb,c='r',label='Navie Bayer Classification')
plt.scatter(y_test,y_pred_rf,c='b',label='Random Forest Classification')
plt.scatter(y_test,y_pred_xgb,c='m',label='XGBoost Classification')
plt.xlabel('Actual Target')
plt.ylabel('Predicated Target')
plt.title('Actual Target Vs Predicated Target')
plt.legend()
plt.show()
```



In [ ]: