visadata-ml-model-creation

October 12, 2023

[ ]:
```
''' working on the visa data to know that the applied persons visa is certified
↪or denied'''
```

1 importing the required packages

[1]:
```
import os
os.getcwd()
```

[1]:
```
'C:\\Users\\DELL\\Documents\\EDA_Model_visadataset'
```

[2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

2 Reading the data

[3]:
```
df=pd.read_csv('Visadataset.csv')
df.head(4)
```

[3]:

	case_id	continent	education_of_employee	has_job_experience	requires_job_training	no_of_employees	yr_of_estab	region_of_employment	prevailing_wage	unit_of_wage	full_time_position	case_status
0	EZYV01	Asia	High School	N	N	14513	2007	West	592.2029	Hour	Y	Denied
1	EZYV02	Asia	Master's	Y	N	2412	2002	Northeast	83425.6500	Year	Y	Certified
2	EZYV03	Asia	Bachelor's	N	Y	44444	2008	West				
3	EZYV04	Asia	Bachelor's	N	N	98	1897	West				

```
2       122996.8600         Year                    Y       Denied
3        83434.0300         Year                    Y       Denied
```

3 data inspection

[4]:
```
df.shape
```

[4]:
```
(25480, 12)
```

[5]:
```
df.dtypes
```

[5]:
```
case_id                 object
continent               object
education_of_employee   object
has_job_experience      object
requires_job_training   object
no_of_employees          int64
yr_of_estab              int64
region_of_employment    object
prevailing_wage        float64
unit_of_wage            object
full_time_position      object
case_status             object
dtype: object
```

[6]:
```
#here--rows=25480,
#----columns=12 columns
```

[7]:
```
#here case id has the unique values so drop the column
```

[8]:
```
df['case_id'].nunique()
```

[8]:
```
25480
```

[9]:
```
df=df.drop('case_id',axis=1)
df.shape
```

[9]:
```
(25480, 11)
```

4 null values checking

[10]:
```
#checking the nulll values
df.isnull().sum()
```

[10]:
```
continent                0
education_of_employee    0
has_job_experience       0
requires_job_training    0
no_of_employees          0
yr_of_estab              0
region_of_employment     0
prevailing_wage          0
unit_of_wage             0
full_time_position       0
case_status              0
dtype: int64
```

[11]:
```
# no null values we can work on the data
```

[12]:
```
cat,num=[],[]
for keys,values in (df.dtypes).items():
    if values=='O':
        cat.append(keys)
    else:
        num.append(keys)
```

5 categorical numerical columns separation

[13]:
```
cat
```

[13]:
```
['continent',
 'education_of_employee',
 'has_job_experience',
 'requires_job_training',
 'region_of_employment',
 'unit_of_wage',
 'full_time_position',
 'case_status']
```

[14]:
```
len(cat)
#we have 8 categorical columns
```

[14]:
```
8
```

[15]:
```
num
#we have only the 3 columns of numerical data
```

[15]:
```
['no_of_employees', 'yr_of_estab', 'prevailing_wage']
```

[16]:
```
df.describe()
```

[16]:

	no_of_employees	yr_of_estab	prevailing_wage
count	25480.000000	25480.000000	25480.000000
mean	5667.043210	1979.409929	74455.814592
std	22877.928848	42.366929	52815.942327
min	-26.000000	1800.000000	2.136700
25%	1022.000000	1976.000000	34015.480000
50%	2109.000000	1997.000000	70308.210000
75%	3504.000000	2005.000000	107735.512500
max	602069.000000	2016.000000	319210.270000

6 correlation

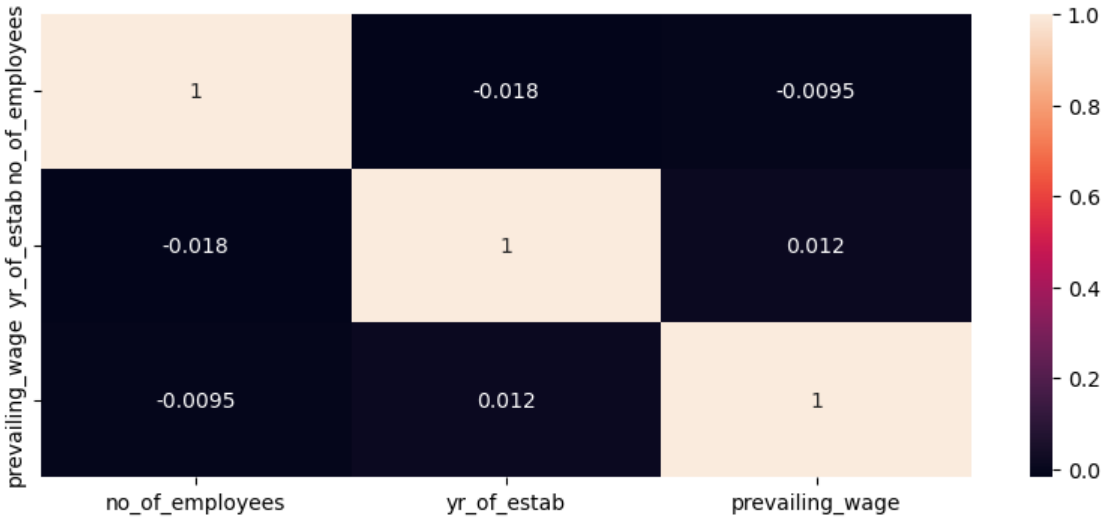
[17]:
```
cor=df.corr()
```

```
C:\Users\DELL\AppData\Local\Temp\ipykernel_5228\960497222.py:1: FutureWarning:
The default value of numeric_only in DataFrame.corr is deprecated. In a future
version, it will default to False. Select only valid columns or specify the
value of numeric_only to silence this warning.
  cor=df.corr()
```

7 Heat map

[18]:
```
plt.figure(figsize=(10, 4))
sns.heatmap(cor, fmt='.2g', annot=True)
```

[18]: <Axes: >

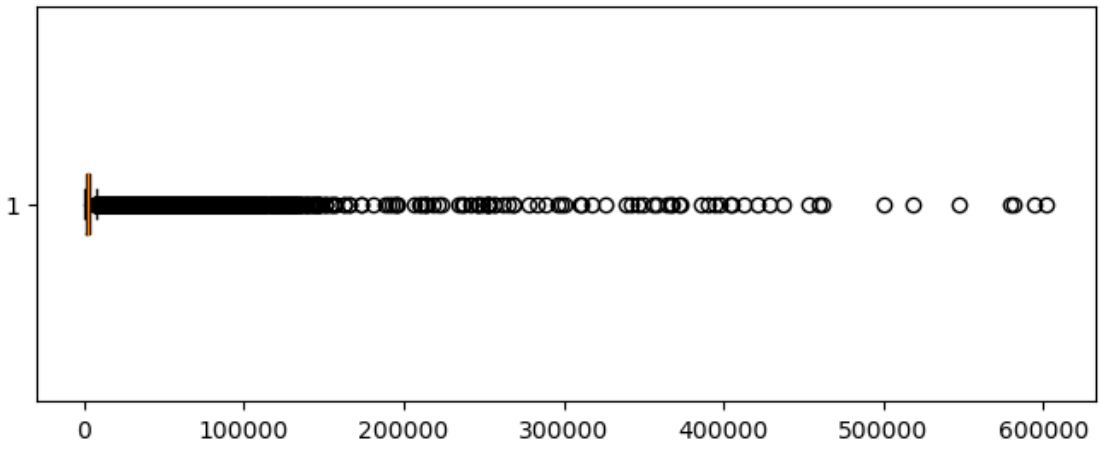


8 Dealing with Outliers

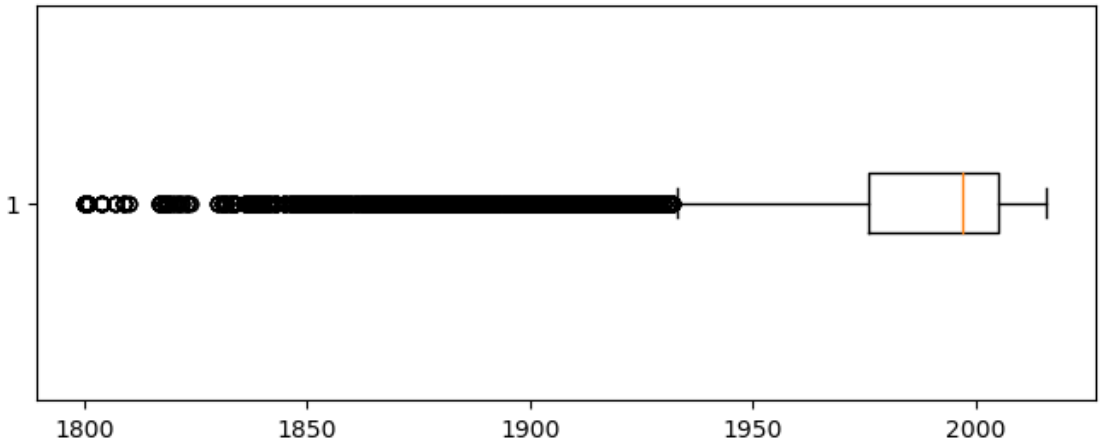
[19]:
```
# using the z-score method checking the outliers in the data
```

9 box plot to visualize the outliers

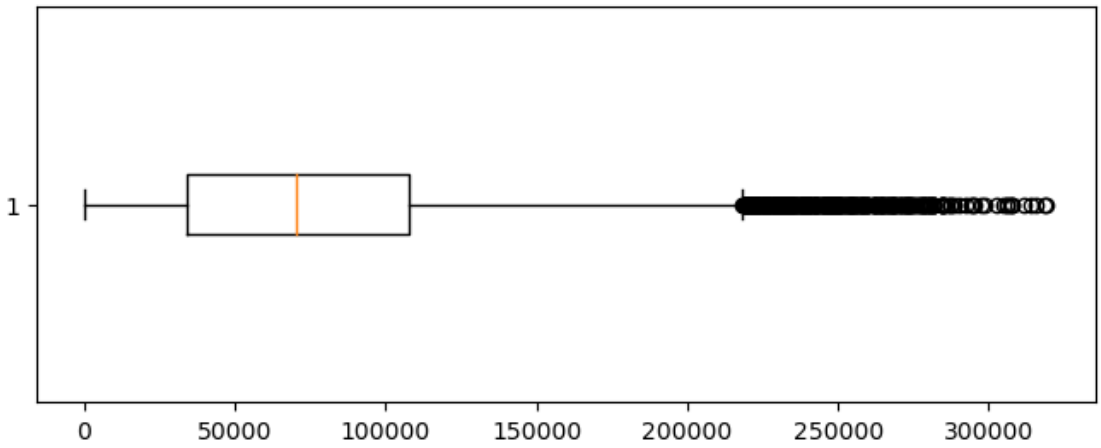
[20]:
```
# box plots-for outliers-----run this code--pending....
plt.figure(figsize=(8,3))
plt.boxplot(df['no_of_employees'],vert=False)
plt.show()
```



[21]:
```
plt.figure(figsize=(8,3))
plt.boxplot(df['yr_of_estab'],vert=False)
plt.show()
```



[22]:
```
plt.figure(figsize=(8,3))
plt.boxplot(df['prevailing_wage'],vert=False)
plt.show()
```



10 importing the package to find the outliers

[23]:
```
from scipy import stats

columns=['no_of_employees', 'yr_of_estab', 'prevailing_wage']

z_scores = np.abs(stats.zscore(df[columns]))

z_score_threshold=3

outlier_indices = np.where(z_scores > z_score_threshold)[0]

df = df.drop(df.index[outlier_indices])
```

[24]:
```
df.shape
```

[24]: (24097, 11)

[25]:
```
#25480-original data set rows

#24097-after droping the outliers rows
```

[26]:
```
25480-24097
```

[26]: 1383

[27]:
```
(1383/25480)*100
#5% of the rows was  droped
```

[27]: 5.42778649921507

11 heat map and corelation after clearing the outliers

[28]:
```
cor1=df.corr()
cor1
```

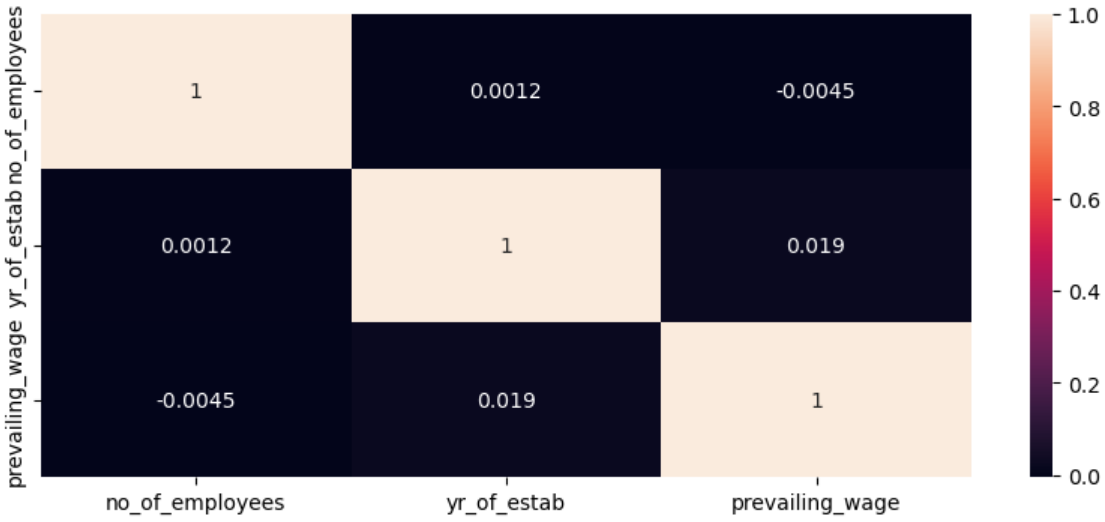
```
C:\Users\DELL\AppData\Local\Temp\ipykernel_5228\3883913210.py:1: FutureWarning:
The default value of numeric_only in DataFrame.corr is deprecated. In a future
version, it will default to False. Select only valid columns or specify the
value of numeric_only to silence this warning.
  cor1=df.corr()
```

[28]:

	no_of_employees	yr_of_estab	prevailing_wage
no_of_employees	1.000000	0.001187	-0.004514
yr_of_estab	0.001187	1.000000	0.019285
prevailing_wage	-0.004514	0.019285	1.000000

[29]:
```
plt.figure(figsize=(10,4))
sns.heatmap(cor1, fmt='.2g', annot=True)
```

[29]: <Axes: >



12 categorical to numerical column

[30]:
```
for categorical in cat:
    from sklearn.preprocessing import LabelEncoder  # Import the package
    le=LabelEncoder()  # save the package
    df[categorical]=le.fit_transform(df[categorical]) # Apply fit transform
```

[31]:
```
df.head(4)
```

[31]:

	continent	education_of_employee	has_job_experience	requires_job_training	no_of_employees	yr_of_estab	region_of_employment	prevailing_wage	unit_of_wage	full_time_position	case_status
0	1	2	0	0	14513	2007	4	592.2029	0	1	1
1	1	3	1	0	2412	2002	2	83425.6500	3	1	0
2	1	0	0	1	44444	2008	4	122996.8600	3	1	1
3	1	0	0	0	98	1897	4	83434.0300	3	1	1

[32]:
```
df1= pd.DataFrame(df)

df1.to_csv('Visadata_preprocessed.csv', index=False)
```

[33]:
```
df1=pd.read_csv('Visadata_preprocessed.csv')
df1.head(4)
```

[33]:

	continent	education_of_employee	has_job_experience	requires_job_training	no_of_employees	yr_of_estab	region_of_employment	prevailing_wage	unit_of_wage	full_time_position	case_status
0	1	2	0	0	14513	2007	4	592.2029	0	1	1
1	1	3	1	0	2412	2002	2	83425.6500	3	1	0
2	1	0	0	1	44444	2008	4	122996.8600	3	1	1
3	1	0	0	0	98	1897	4	83434.0300	3	1	1

```
0          592.2029              0                    1              1
1        83425.6500              3                    1              0
2       122996.8600              3                    1              1
3        83434.0300              3                    1              1
```

[34]:
```
df1.shape
```

[34]:
```
(24097, 11)
```

13 seaparating the data into input-X and output-y

[35]:
```
X=df.drop('case_status',axis=1)
y=df['case_status']
```

14 feature selection using the -Mutual Info Clasifi method

[36]:
```
from sklearn.feature_selection import mutual_info_classif
MI=mutual_info_classif(X,y)
MI
```

[36]:
```
array([0.00662145, 0.05120086, 0.02033962, 0.00612655, 0.00235631,
       0.00388416, 0.01092362, 0.01409298, 0.02226787, 0.0043269 ])
```

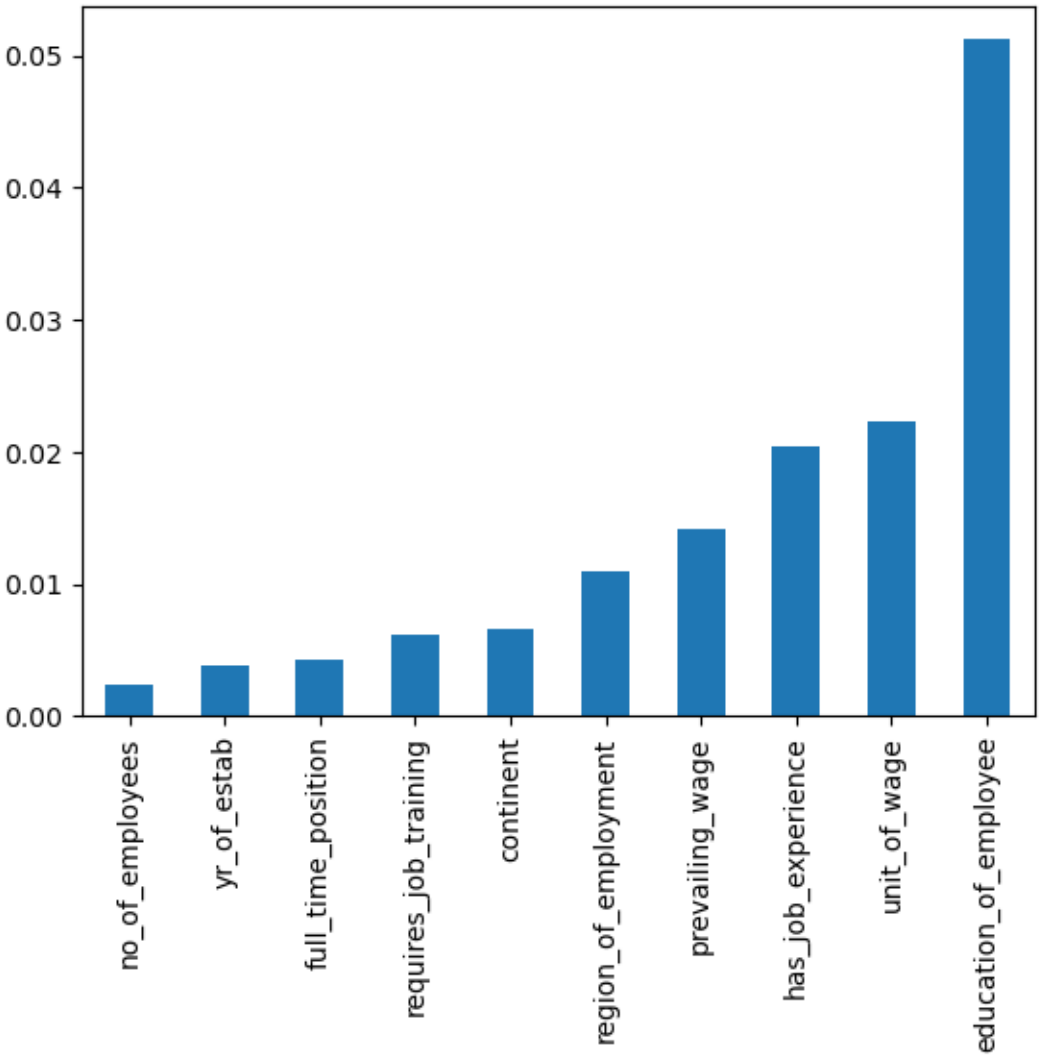
[37]:
```
value=pd.Series(MI)
value.index=X.columns
```

[38]:
```
value.sort_values(ascending=True)
```

[38]:
```
no_of_employees          0.002356
yr_of_estab              0.003884
full_time_position       0.004327
requires_job_training    0.006127
continent                0.006621
region_of_employment     0.010924
prevailing_wage          0.014093
has_job_experience       0.020340
unit_of_wage             0.022268
education_of_employee    0.051201
dtype: float64
```

[39]:
```
value.sort_values(ascending=True).plot(kind='bar')
```

[39]:
```
<Axes: >
```



[40]:
```
# here droping the requires_job_training column which is very less relation
```

[41]:
```
X.columns
```

[41]:
```
Index(['continent', 'education_of_employee', 'has_job_experience',
       'requires_job_training', 'no_of_employees', 'yr_of_estab',
       'region_of_employment', 'prevailing_wage', 'unit_of_wage',
       'full_time_position'],
      dtype='object')
```

[42]:
```
X=df.drop(['requires_job_training','case_status'],axis=1)
y=df['case_status']
```

15 training the model by Machine leraning algorithms

16 without Hyper parameter Tuning

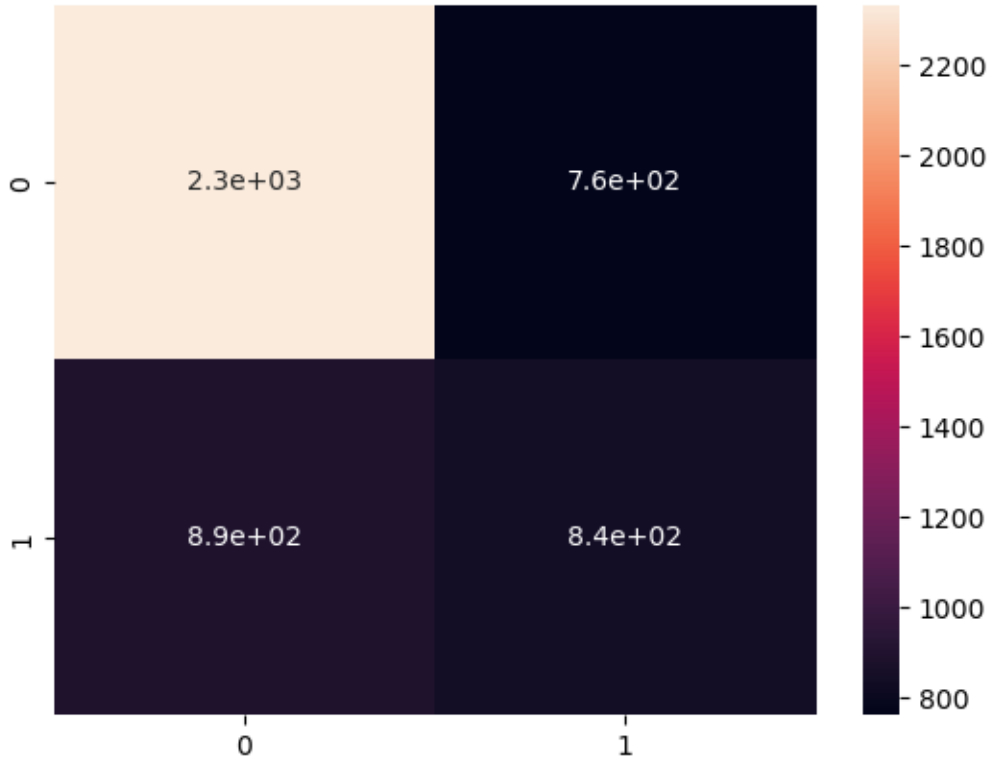
17 Decision Tree-Model-1

[43]:
```
###############---spliting the data-----###############


X=df.drop('case_status',axis=1)
y=df['case_status']

#################---segregating the data into Train data and the test␣
 ↪data----############################


from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,
                                               y,
                                               random_state=0,
                                               test_size=0.2)

####################-----------Fitting the␣
 ↪model-----#####################################

from sklearn.tree import DecisionTreeClassifier
dt=DecisionTreeClassifier()
dt.fit(X_train, y_train)

##################---calculating the model prediction␣
 ↪value-------#################################

y_pred_dt=dt.predict(X_test)
y_pred_dt

###################-------importing the package and calculating the␣
 ↪metrics------#################################


from sklearn.metrics import␣
 ↪accuracy_score,precision_score,recall_score,f1_score,classification_report
from sklearn.metrics import confusion_matrix,ConfusionMatrixDisplay

dtree_cmt=confusion_matrix(y_pred_dt,y_test)
dtree_cmt
sns.heatmap(dtree_cmt,annot=True)
```

```
####################----calculating  the metrics for clasification␣
 ↪algorithn-----##############################

dt_metrics={}
dt_metrics['accuracy']=round(accuracy_score(y_pred_dt,y_test)*100,2)
dt_metrics['precision']=round(precision_score(y_pred_dt,y_test)*100,2)
dt_metrics['recall']=round(recall_score(y_pred_dt,y_test)*100,2)
dt_metrics['f1_score']=round(f1_score(y_pred_dt,y_test)*100,2)
dt_metrics

dt_metrics_df=pd.DataFrame(dt_metrics,index=['Decision Tree'])
dt_metrics_df
```

[43]:

	accuracy	precision	recall	f1_score
Decision Tree	65.77	52.32	48.43	50.3



[ ]:

18 K-nearest Neighbours-Model-2

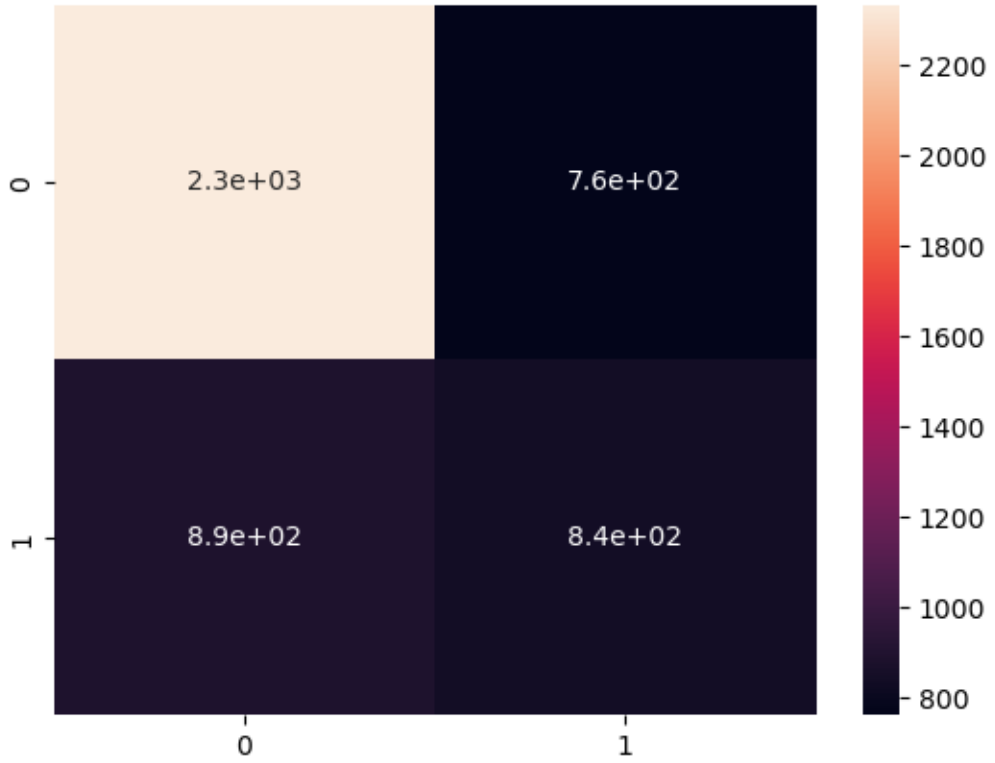
[44]:
```
###############---spliting the data-----###############

X=df.drop('case_status',axis=1)
y=df['case_status']

#################---segregating the data into Train data and the test␣
 ↪data----############################

from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,
                                               y,
                                               random_state=0,
                                               test_size=0.2)
##################--fitting the␣
 ↪model-------#####################################
from sklearn.neighbors import KNeighborsClassifier
KNN=KNeighborsClassifier()
KNN.fit(X_train, y_train)

##################--calculating the model predicted␣
 ↪value----#################################

y_pred_KNN=KNN.predict(X_test.values)
y_pred_KNN

#####################----calculating the␣
 ↪metrics---===############################
from sklearn.metrics import␣
 ↪accuracy_score,precision_score,recall_score,f1_score,classification_report
from sklearn.metrics import confusion_matrix,ConfusionMatrixDisplay

KNN_cmt=confusion_matrix(y_pred_dt,y_test)
KNN_cmt

sns.heatmap(KNN_cmt,annot=True)
#####################-----creating the data frame for the metrics␣
 ↪value-----############################

KNN_metrics={}
KNN_metrics['accuracy']=round(accuracy_score(y_pred_KNN,y_test)*100,2)
KNN_metrics['precision']=round(precision_score(y_pred_KNN,y_test)*100,2)
KNN_metrics['recall']=round(recall_score(y_pred_KNN,y_test)*100,2)
KNN_metrics['f1_score']=round(f1_score(y_pred_KNN,y_test)*100,2)
KNN_metrics
```

```
KNN_metrics_df=pd.DataFrame(KNN_metrics,index=['KNN'])
KNN_metrics_df
```

```
C:\Users\DELL\anaconda3\Lib\site-packages\sklearn\base.py:464: UserWarning: X
does not have valid feature names, but KNeighborsClassifier was fitted with
feature names
  warnings.warn(
```

[44]:

	accuracy	precision	recall	f1_score
KNN	63.36	27.69	41.94	33.36



[ ]:

19 Navie bayes-Model-3

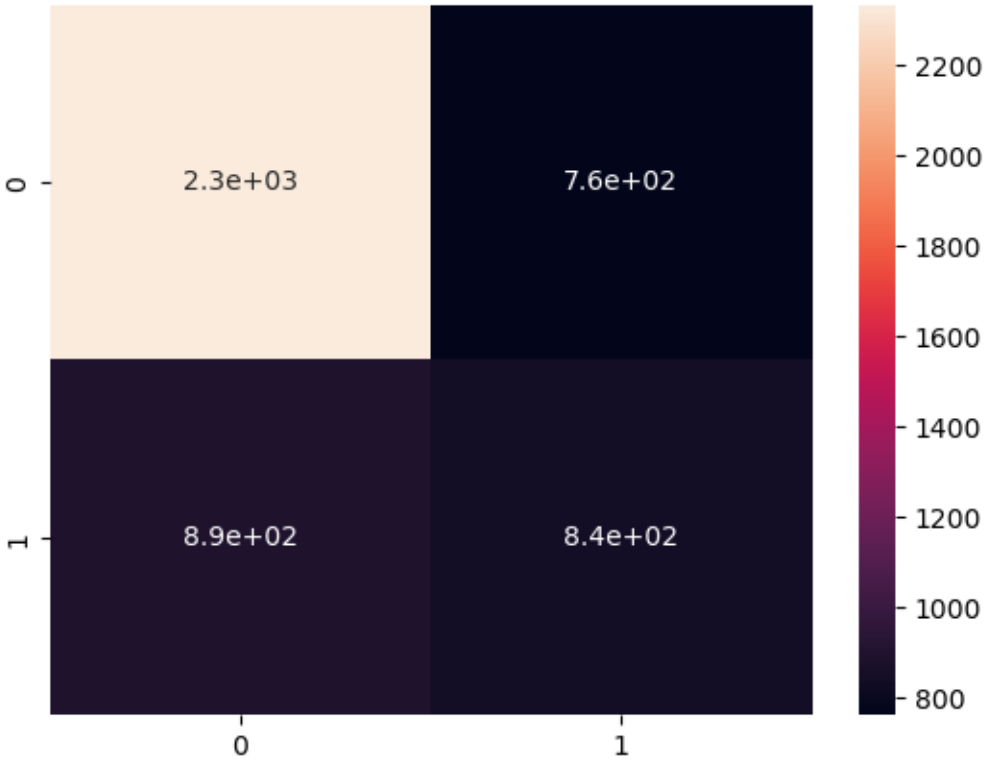
[45]:
```
###############------splitting the data-----#######################

X=df.drop('case_status',axis=1)
y=df['case_status']
```

```
####################---segregating the data into Train data and the test␣
 ↪data----##########

from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,
                                               y,
                                               random_state=0,
                                               test_size=0.2)
#####################----Fitting the␣
 ↪model---------##############################
from sklearn.naive_bayes import GaussianNB
NB=GaussianNB()
NB.fit(X_train, y_train)

######################-----calculating the model predicted␣
 ↪value-----------------############################

y_pred_NB=NB.predict(X_test.values)
y_pred_NB

######################--------calculating the␣
 ↪metrics-------------############################
from sklearn.metrics import␣
 ↪accuracy_score,precision_score,recall_score,f1_score,classification_report
from sklearn.metrics import confusion_matrix,ConfusionMatrixDisplay

NB_cmt=confusion_matrix(y_pred_dt,y_test)
NB_cmt

sns.heatmap(NB_cmt,annot=True)

###################-----creating the data frame for the calculated␣
 ↪metrics--------##############################

NB_metrics={}
NB_metrics['accuracy']=round(accuracy_score(y_pred_NB,y_test)*100,2)
NB_metrics['precision']=round(precision_score(y_pred_NB,y_test)*100,2)
NB_metrics['recall']=round(recall_score(y_pred_NB,y_test)*100,2)
NB_metrics['f1_score']=round(f1_score(y_pred_NB,y_test)*100,2)
NB_metrics

NB_metrics_df=pd.DataFrame(NB_metrics,index=['Navie Bayes'])
NB_metrics_df
```

```
C:\Users\DELL\anaconda3\Lib\site-packages\sklearn\base.py:464: UserWarning: X
does not have valid feature names, but GaussianNB was fitted with feature names
  warnings.warn(
```

[45]:

	accuracy	precision	recall	f1_score
Navie Bayes	69.05	15.48	63.33	24.87



[ ]:

20 Logistic Regressio-Model-4

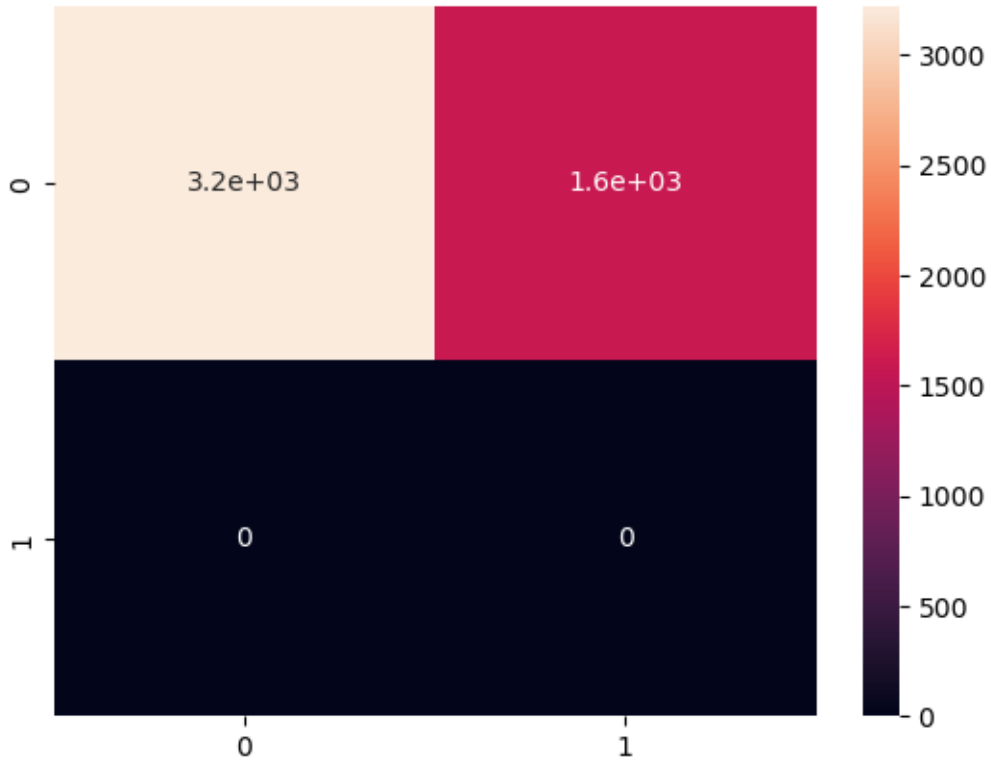
[46]:
```
#################-----splitting the data-----######################

X=df.drop('case_status',axis=1)
y=df['case_status']

##################-----model selection---------#########################

from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,
                                               y,
                                               random_state=0,
                                               test_size=0.2)
###################-------------fitting the␣
 ↪model--------#################################
```

```
from sklearn.linear_model import LogisticRegression
LG=LogisticRegression()
LG.fit(X_train, y_train)

##################---calculating the model predicted␣
 ↪value---------------###############################

y_pred_LG=LG.predict(X_test.values)
y_pred_LG

###################----calculating the␣
 ↪metrics-----------###############################
from sklearn.metrics import␣
 ↪accuracy_score,precision_score,recall_score,f1_score,classification_report
from sklearn.metrics import confusion_matrix,ConfusionMatrixDisplay

LG_cmt=confusion_matrix(y_pred_LG,y_test)
LG_cmt

sns.heatmap(LG_cmt,annot=True)
####################--------------creating the data frame for the calculated␣
 ↪metrics------------############################

LG_metrics={}
LG_metrics['accuracy']=round(accuracy_score(y_pred_LG,y_test)*100,2)
LG_metrics['precision']=round(precision_score(y_pred_LG,y_test)*100,2)
LG_metrics['recall']=round(recall_score(y_pred_LG,y_test)*100,2)
LG_metrics['f1_score']=round(f1_score(y_pred_LG,y_test)*100,2)
LG_metrics

LG_metrics_df=pd.DataFrame(LG_metrics,index=['Logistic Regression'])
LG_metrics_df
```

```
C:\Users\DELL\anaconda3\Lib\site-packages\sklearn\base.py:464: UserWarning: X
does not have valid feature names, but LogisticRegression was fitted with
feature names
  warnings.warn(
C:\Users\DELL\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1469: UndefinedMetricWarning: Recall
is ill-defined and being set to 0.0 due to no true samples. Use `zero_division`
parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

[46]:

	accuracy	precision	recall	f1_score
Logistic Regression	66.89	0.0	0.0	0.0



[ ]:

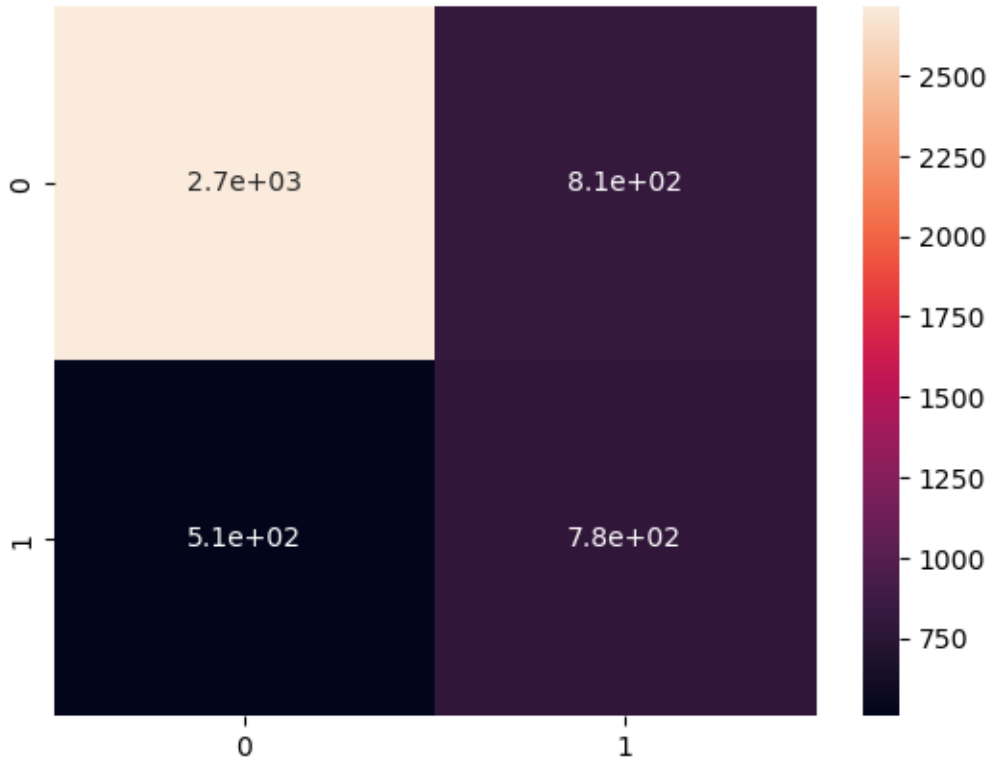
21 Random Forest-Model-5

[47]:
```
#################----------splitting the data into input-X and the␣
 ↪ouput-y--------############333

X=df.drop('case_status',axis=1)
y=df['case_status']


################----------model␣
 ↪selction----------###############################
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,
                                               y,
                                               random_state=0,
                                               test_size=0.2)
########################--------model␣
 ↪training-----------#######################################
from sklearn.ensemble import RandomForestClassifier
```

```
RF=RandomForestClassifier()
RF.fit(X_train,y_train)

#################---------calculating the model predicted␣
 ↪value---------################


y_pred_RF=RF.predict(X_test)
y_pred_RF

##################-------calculating the metrics in␣
 ↪classification-------###############################
from sklearn.metrics import␣
 ↪accuracy_score,precision_score,recall_score,f1_score,classification_report
from sklearn.metrics import confusion_matrix,ConfusionMatrixDisplay

RF_cmt=confusion_matrix(y_pred_RF,y_test)
RF_cmt
sns.heatmap(RF_cmt,annot=True)

#################-------------creating the data frame for the calculated␣
 ↪accuracy-------###############################

RF_metrics={}
RF_metrics['accuracy']=round(accuracy_score(y_pred_RF,y_test)*100,2)
RF_metrics['precision']=round(precision_score(y_pred_RF,y_test)*100,2)
RF_metrics['recall']=round(recall_score(y_pred_RF,y_test)*100,2)
RF_metrics['f1_score']=round(f1_score(y_pred_RF,y_test)*100,2)
RF_metrics

RF_metrics_df=pd.DataFrame(RF_metrics,index=['Random Forest'])
RF_metrics_df
```

[47]:

	accuracy	precision	recall	f1_score
Random Forest	72.66	49.12	60.78	54.33



22 creating the data frame for the metrics calculated in the clasification models

[48]:
```
Metrics_df = pd.
↪concat([RF_metrics_df,NB_metrics_df,LG_metrics_df,NB_metrics_df,dt_metrics_df],␣
↪axis=0)
```

[49]:
```
Metrics_df
```

[49]:

	accuracy	precision	recall	f1_score
Random Forest	72.66	49.12	60.78	54.33
Navie Bayes	69.05	15.48	63.33	24.87
Logistic Regression	66.89	0.00	0.00	0.00
Navie Bayes	69.05	15.48	63.33	24.87
Decision Tree	65.77	52.32	48.43	50.30

[ ]:
```

```