Room Occupancy Detection.

Room occupancy classification (ROC) is a type of time series classification problem where the goal is to predict whether a room is occupied or not based on a sequence of time series data, such as temperature and humidity. ROC is a common problem in smart buildings, where it can be used to control various systems, such as the HVAC system, lighting system, and security system.

In [60]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Loading two datasets and combining into one.

In [61]:
```
#loading the datasets
df1 = pd.read_csv('datatest1.csv')
df2 = pd.read_csv('datatraining.csv')
```

In [62]:
```
room = pd.concat([df1 , df2])
room
```

Out[62]:

	date	Temperature	Humidity	Light	CO2	HumidityRatio	Occupancy
140	2015-02-02 14:19:00	23.7000	26.2720	585.200000	749.200000	0.004764	1
141	2015-02-02 14:19:59	23.7180	26.2900	578.400000	760.400000	0.004773	1
142	2015-02-02 14:21:00	23.7300	26.2300	572.666667	769.666667	0.004765	1
143	2015-02-02 14:22:00	23.7225	26.1250	493.750000	774.750000	0.004744	1
144	2015-02-02 14:23:00	23.7540	26.2000	488.600000	779.000000	0.004767	1
...	...	...	...	...	...	...	...
8139	2015-02-10 09:29:00	21.0500	36.0975	433.000000	787.250000	0.005579	1
8140	2015-02-10 09:29:59	21.0500	35.9950	433.000000	789.500000	0.005563	1
8141	2015-02-10 09:30:59	21.1000	36.0950	433.000000	798.500000	0.005596	1
8142	2015-02-10 09:32:00	21.1000	36.2600	433.000000	820.333333	0.005621	1
8143	2015-02-10 09:33:00	21.1000	36.2000	447.000000	821.000000	0.005612	1

10808 rows × 7 columns

Data Preprocessing

In [63]:
```
#number of rows and columns
room.shape
```

Out[63]:
```
(10808, 7)
```

In [64]:
```
#checking for null values
room.isnull().sum()
```

Out[64]:
```
date             0
Temperature      0
Humidity         0
Light            0
CO2              0
HumidityRatio    0
Occupancy        0
dtype: int64
```

In [65]:
```
#checking for duplicate values
room.duplicated().sum()
```

Out[65]:
```
0
```

In [66]:
```
#removing the duplicate values
room.drop_duplicates(inplace=True)
```

In [67]:
```
#checking data types
room.dtypes
```

```
Out[67]: date               object
         Temperature       float64
         Humidity          float64
         Light             float64
         CO2               float64
         HumidityRatio     float64
         Occupancy           int64
         dtype: object
```

```
In [68]: #converting the date and time to datetime format
         room['date'] = pd.to_datetime(room['date'])
```

```
In [69]: room.dtypes
```

```
Out[69]: date             datetime64[ns]
         Temperature             float64
         Humidity                float64
         Light                   float64
         CO2                     float64
         HumidityRatio           float64
         Occupancy                 int64
         dtype: object
```

```
In [70]: #checking the descriptive statistics
         room.describe()
```

Out[70]:

	Temperature	Humidity	Light	CO2	HumidityRatio	Occupancy
count	10808.000000	10808.000000	10808.000000	10808.00000	10808.000000	10808.000000
mean	20.819992	25.638407	137.694088	634.00507	0.003903	0.249907
std	1.078410	4.953792	212.175483	312.81727	0.000803	0.432979
min	19.000000	16.745000	0.000000	412.75000	0.002674	0.000000
25%	20.000000	21.390000	0.000000	441.00000	0.003323	0.000000
50%	20.700000	25.680000	0.000000	464.00000	0.003805	0.000000
75%	21.500000	28.324167	413.541667	761.00000	0.004372	0.000000
max	24.408333	39.117500	1697.250000	2028.50000	0.006476	1.000000

```
In [71]: #value counts for the target variable i.e. occupancy
         room['Occupancy'].value_counts()
```

```
Out[71]: 0    8107
         1    2701
         Name: Occupancy, dtype: int64
```

Correlation between the variables

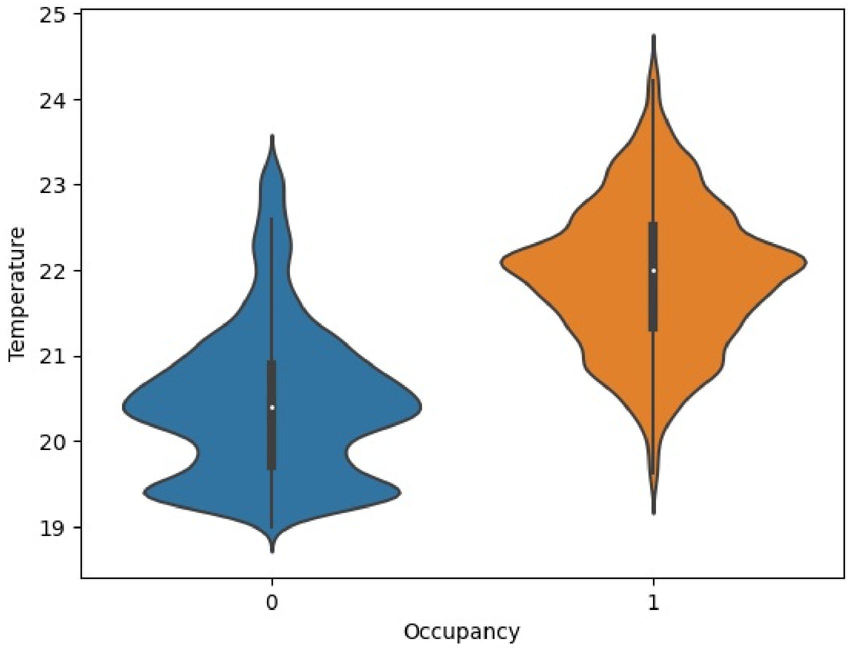
Correlation Heatmap

```
In [72]: # Correlation Heatmap
         plt.figure(figsize = (20,10))
         sns.heatmap(room.corr(),annot = True)
         plt.show()
```

There is a strong coorelation between light and occupancy as well as between humidity and humidity ratio. The co2 levels and temperature also shows a strong correlation with the occupancy. However the humidity and humidity ratio has very less correlation with the occupancy.

Temperature and Occupancy

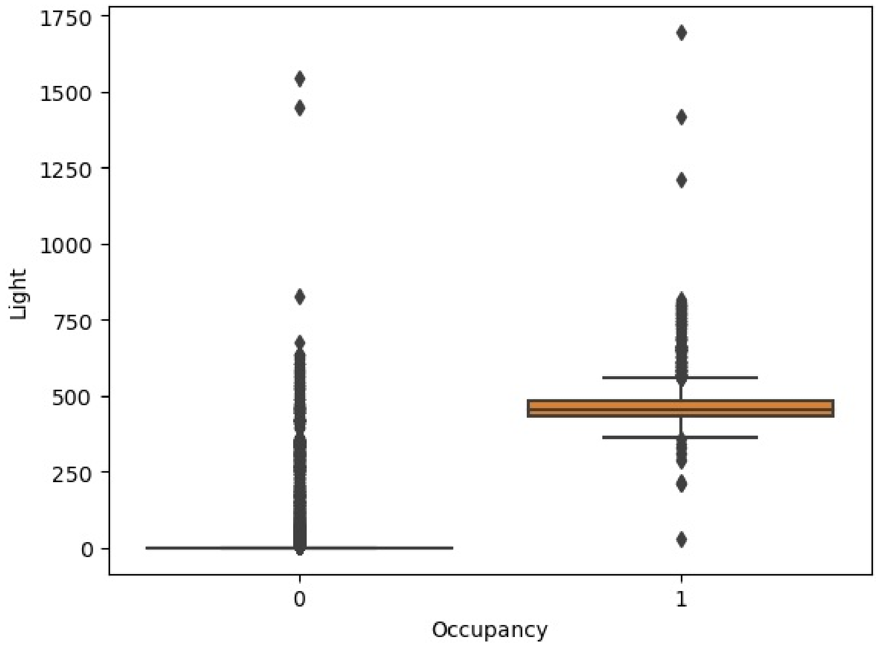
In [73]:
```
# Violineplot for Temperature

sns.violinplot(y = room['Temperature'], x = room['Occupancy'])
plt.xlabel('Occupancy')
plt.ylabel('Temperature')
plt.show()
```



The temperature and occupancy graph shows that the temperature of the room increases when there is a person in the room. This is because of the heat emitted by the human body. The temperature of the room decreases when there is no person in the room. This proves the hypothesis regarding the peaks in the temperature graph.

Light and Occupancy

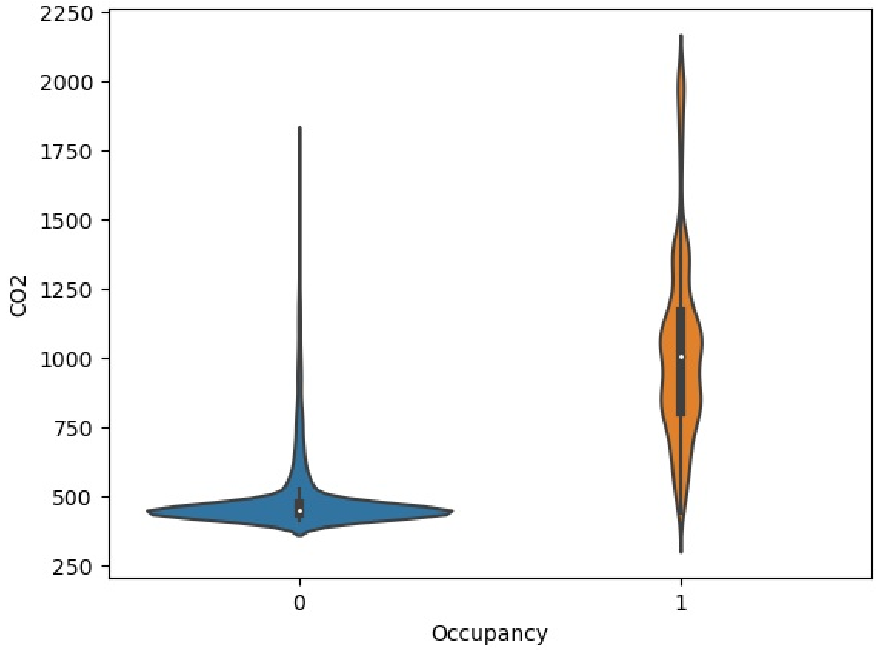
In [74]:
```
# Boxplot for Light

sns.boxplot(y = room['Light'], x = room['Occupancy'])
plt.xlabel('Occupancy')
plt.ylabel('Light')
plt.show()
```



The light intensity of the room increases when there is a person in the room. This is because the lights are turned on when there is a person in the room. The light intensity of the room decreases when there is no person in the room. This proves the hypothesis regarding the peaks in the light graph. The outliers in the boxplot and the curves in the ligh graph might be due to sunlight entering the room.

CO2 and Occupancy

In [75]:
```
#violinlot for co2
sns.violinplot(y = room['CO2'],x = room['Occupancy'])
plt.xlabel('Occupancy')
plt.ylabel('CO2')
plt.show()
```



The CO2 levels of the room increases when there is a person in the room. This is because of the CO2 emitted by the human body. The CO2 levels of the room decreases when there is no person in the room. This proves the hypothesis regarding the peaks in the CO2 graph. From the above EDA, it is quite clear that the temperature, light and CO2 levels of the room are a good indicator of the occupancy of the room. Therefore we will be using these three variables for our classification model.

Data Preprocessing 2

In [76]:
```
#dropping columns humidity, date and humidity ratio
room.drop(['Humidity','date','HumidityRatio'],axis=1,inplace=True)
```

In [77]:
```
room.head(10)
```

Out[77]:

	Temperature	Light	CO2	Occupancy
140	23.7000	585.200000	749.200000	1
141	23.7180	578.400000	760.400000	1
142	23.7300	572.666667	769.666667	1
143	23.7225	493.750000	774.750000	1
144	23.7540	488.600000	779.000000	1
145	23.7600	568.666667	790.000000	1
146	23.7300	536.333333	798.000000	1
147	23.7540	509.000000	797.000000	1
148	23.7540	476.000000	803.200000	1
149	23.7360	510.000000	809.000000	1

Train Test Split

In [78]:
```
from sklearn.model_selection import train_test_split
```

In [79]:
```
x_train, x_test, y_train, y_test = train_test_split(room.drop(['Occupancy'],axis=1),room['Occupancy'],test_size
```

Model Building

Random Tree Classifier

In [80]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [81]:
```
rfc = RandomForestClassifier()
rfc
```

Out[81]:
```
RandomForestClassifier()
```

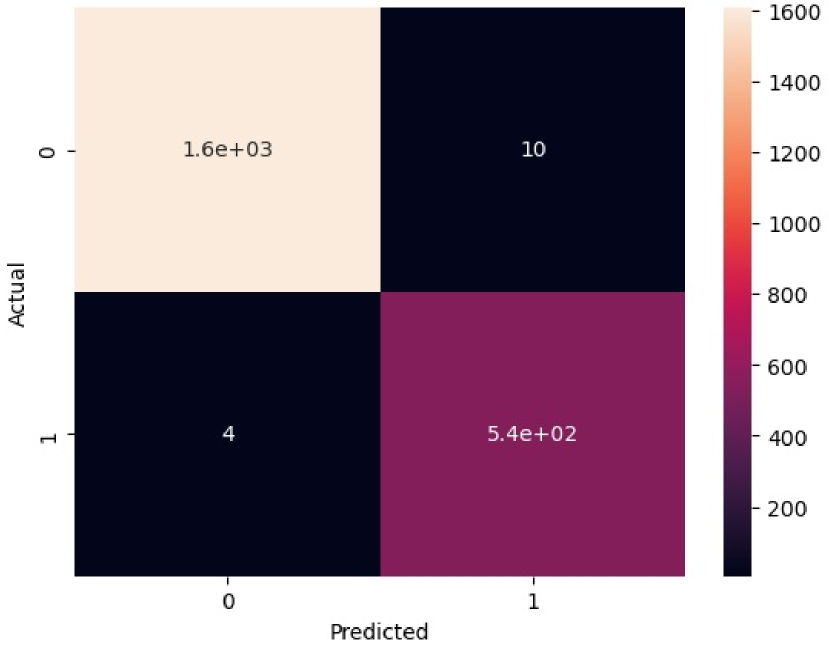
In [82]:
```
#training the model
rfc.fit(x_train,y_train)
#training accuracy
rfc.score(x_train,y_train)
```

Out[82]:
```
1.0
```

Model Evaluation

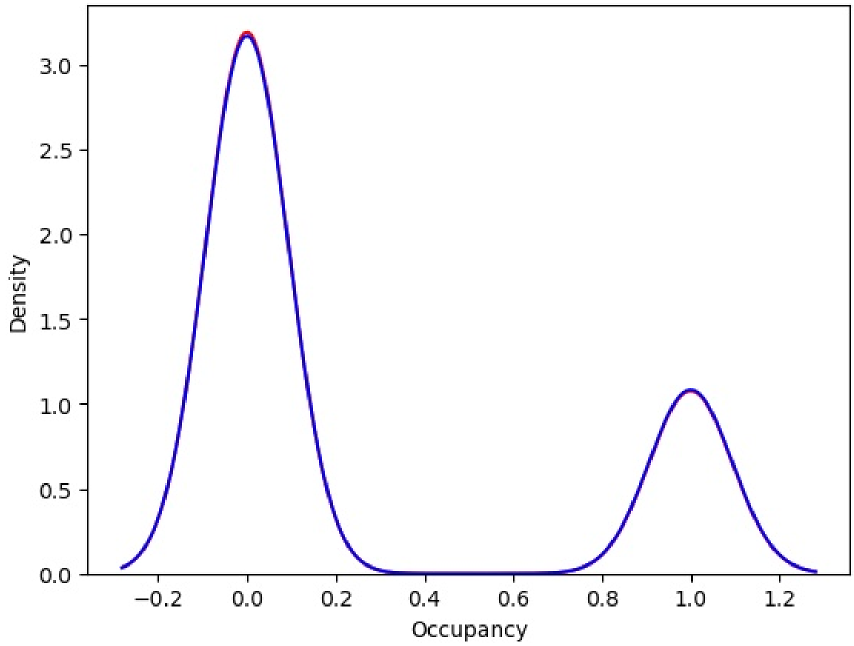
In [83]:
```
rfc_pred = rfc.predict(x_test)
```

In [85]:
```
# Confusion metrix Heatmap.

from sklearn.metrics import confusion_matrix
sns.heatmap(confusion_matrix(y_test, rfc_pred), annot = True)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```



In [86]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [92]:
```
# Distributed plot for the predicted and actual values

ax = sns.distplot(y_test, hist = False, label = 'Actual', color = 'r')
sns.distplot(rfc_pred, hist = False, label = 'Predicted', color = 'b', ax = ax)
plt.show()
```



The distplot function in Python is used to show actual and predicted values because it provides a visually appealing and easy-to-interpret way to compare the two distributions. The distplot function plots a kernel density estimate (KDE) line for each distribution, which is a smooth curve that represents the underlying probability density function of the data. The KDE lines can be used to identify the peaks and valleys in the distributions, as well as the overall shape of the distributions.

In [94]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test, rfc_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      0.99      1.00      1617
           1       0.98      0.99      0.99       545

    accuracy                           0.99      2162
   macro avg       0.99      0.99      0.99      2162
weighted avg       0.99      0.99      0.99      2162
```

In [95]:
```
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
```

In [98]:
```
print('Accuracy Score : ' +str(accuracy_score(y_test, rfc_pred)))
print('Precision Score : ' +str(precision_score(y_test, rfc_pred)))
print('Recall Score : ' +str(recall_score(y_test, rfc_pred)))
print('F1 Score : '+str(f1_score(y_test, rfc_pred)))
```

```
Accuracy Score : 0.9935245143385754
Precision Score : 0.9818511796733213
Recall Score : 0.9926605504587156
F1 Score : 0.9872262773722629
```

Testing the model on new dataset

In [99]:
```
room_new = pd.read_csv('datatest2.csv')
room_new
```

Out[99]:

	date	Temperature	Humidity	Light	CO2	HumidityRatio	Occupancy
1	2015-02-11 14:48:00	21.7600	31.133333	437.333333	1029.666667	0.005021	1
2	2015-02-11 14:49:00	21.7900	31.000000	437.333333	1000.000000	0.005009	1
3	2015-02-11 14:50:00	21.7675	31.122500	434.000000	1003.750000	0.005022	1
4	2015-02-11 14:51:00	21.7675	31.122500	439.000000	1009.500000	0.005022	1
5	2015-02-11 14:51:59	21.7900	31.133333	437.333333	1005.666667	0.005030	1
...	...	...	...	...	...	...	...
9748	2015-02-18 09:15:00	20.8150	27.717500	429.750000	1505.250000	0.004213	1
9749	2015-02-18 09:16:00	20.8650	27.745000	423.500000	1514.500000	0.004230	1
9750	2015-02-18 09:16:59	20.8900	27.745000	423.500000	1521.500000	0.004237	1
9751	2015-02-18 09:17:59	20.8900	28.022500	418.750000	1632.000000	0.004279	1
9752	2015-02-18 09:19:00	21.0000	28.100000	409.000000	1864.000000	0.004321	1

9752 rows × 7 columns

In [100…
```
# Dropping column humidity, date and humidity ration

room_new.drop(['Humidity', 'date', 'HumidityRatio'], axis = 1, inplace = True)
```

In [103…
```
room_new.head()
```

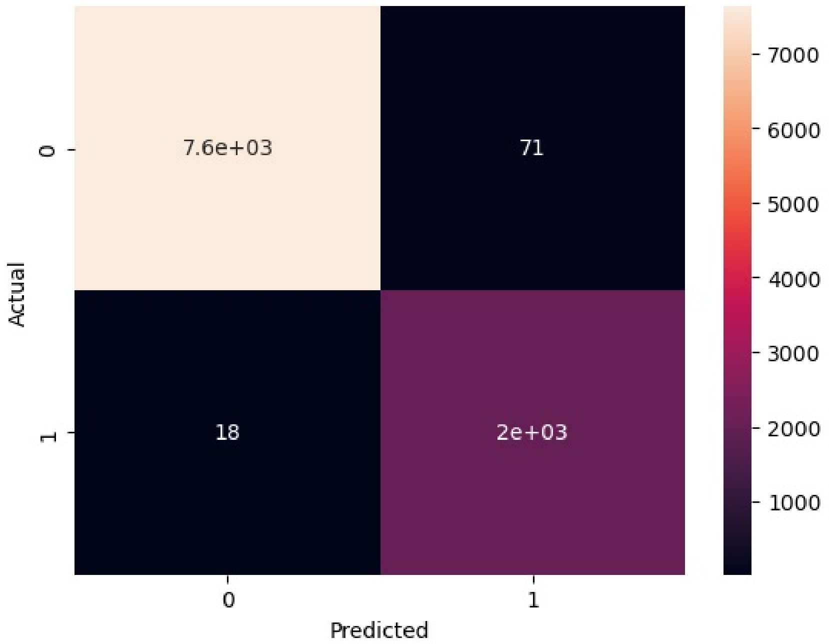
Out[103]:

	Temperature	Light	CO2	Occupancy
1	21.7600	437.333333	1029.666667	1
2	21.7900	437.333333	1000.000000	1
3	21.7675	434.000000	1003.750000	1
4	21.7675	439.000000	1009.500000	1
5	21.7900	437.333333	1005.666667	1

In [104…
```
x = room_new.drop(['Occupancy'], axis = 1)
y = room_new['Occupancy']
```

In [105…
```
#predicting the values
pred = rfc.predict(x)
```

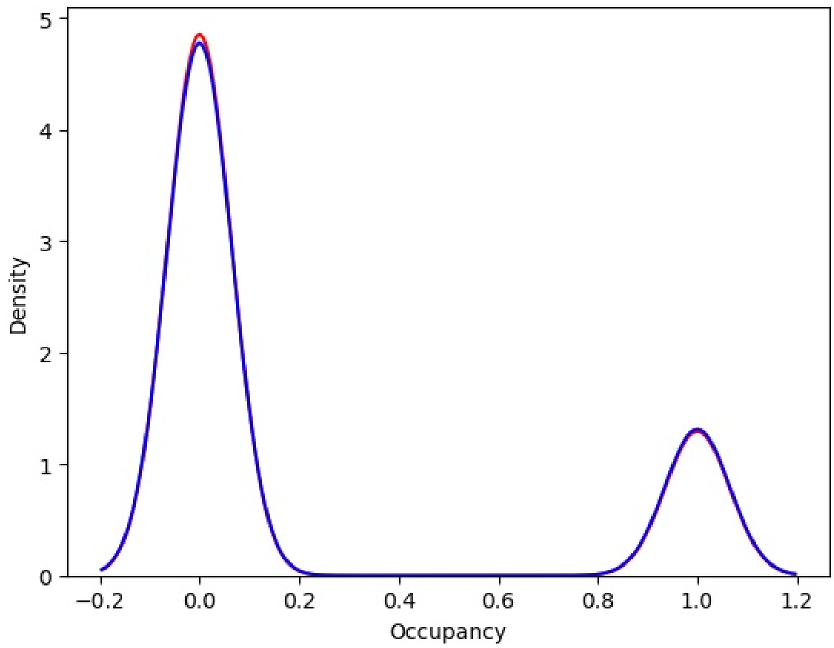
In [106…
```
# Confusion matrix Heatmap

sns.heatmap(confusion_matrix(y,pred), annot = True)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```



A heatmap is a graphical representation of a matrix, where the values in the matrix are represented by colors. The colors are typically chosen to represent different levels of intensity, with darker colors representing higher values. When a confusion matrix is visualized as a heatmap, it is easy to identify which classes are being predicted correctly and incorrectly. The darker colors in the heatmap indicate the classes that are being predicted incorrectly most often.

In [108…

```
# Distribution Plot for the Predicted and an Actual Values:

ax = sns.distplot(y, hist = False, label = 'Actual', color = 'r')
sns.distplot(pred, hist = False, label = 'Predicted', color = 'b')
plt.show()
```



In [109…

```
print(classification_report(y,pred))
```

```
              precision    recall  f1-score   support

           0       1.00      0.99      0.99      7703
           1       0.97      0.99      0.98      2049

    accuracy                           0.99      9752
   macro avg       0.98      0.99      0.99      9752
weighted avg       0.99      0.99      0.99      9752
```

In [110…

```
print('Accuracy Score : ' + str(accuracy_score(y,pred)))
print('Precision Score : ' + str(precision_score(y,pred)))
print('Recall Score : ' + str(recall_score(y,pred)))
print('F1 Score : ' + str(f1_score(y,pred)))
```

```
Accuracy Score : 0.9908736669401148
Precision Score : 0.9662226450999049
Recall Score : 0.9912152269399708
F1 Score : 0.9785593832811372
```

Conclusion

Conclusion

From the above models we can see that the Random Forest Classifier has the highest accuracy score of 99%. Therefore we will be using the Random Forest Classifier for our final model. I also conclude that from the exploratory data analysis, it was found that the change in room temperature, CO levels and light intensity can be used to predict the occupancy of the room, inplace of humidity and humidity ratio.

In [ ]:

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