

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn import svm
from sklearn.ensemble import RandomForestClassifier
from sklearn import model_selection
from sklearn.metrics import accuracy_score
```

```
df=pd.read_csv("Employee attrition data.csv")
df.head()
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	
1	49	No	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	Other	1	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	
4	27	No	Travel_Rarely	591	Research & Development	2	1	Medical	1	

5 rows × 35 columns

```
df.describe()
```

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSatisfaction	HourlyRate	...
count	1470.000000	1470.000000	1470.000000	1470.000000	1470.0	1470.000000	1470.000000	1470.000000	
mean	36.923810	802.485714	9.192517	2.912925	1.0	1024.865306	2.721769	65.891156	
std	9.135373	403.509100	8.106864	1.024165	0.0	602.024335	1.093082	20.329428	
min	18.000000	102.000000	1.000000	1.000000	1.0	1.000000	1.000000	30.000000	
25%	30.000000	465.000000	2.000000	2.000000	1.0	491.250000	2.000000	48.000000	
50%	36.000000	802.000000	7.000000	3.000000	1.0	1020.500000	3.000000	66.000000	
75%	43.000000	1157.000000	14.000000	4.000000	1.0	1555.750000	4.000000	83.750000	
max	60.000000	1499.000000	29.000000	5.000000	1.0	2068.000000	4.000000	100.000000	

8 rows × 26 columns

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
Data columns (total 35 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Age                   1470 non-null  int64
1   Attrition             1470 non-null  object
2   BusinessTravel        1470 non-null  object
3   DailyRate             1470 non-null  int64
4   Department            1470 non-null  object
5   DistanceFromHome      1470 non-null  int64
6   Education              1470 non-null  int64
7   EducationField        1470 non-null  object
8   EmployeeCount         1470 non-null  int64
9   EmployeeNumber        1470 non-null  int64
10  EnvironmentSatisfaction 1470 non-null  int64
11  Gender                1470 non-null  object
12  HourlyRate            1470 non-null  int64
13  JobInvolvement        1470 non-null  int64
14  JobLevel              1470 non-null  int64
15  JobRole               1470 non-null  object
16  JobSatisfaction       1470 non-null  int64
17  MaritalStatus         1470 non-null  object
18  MonthlyIncome         1470 non-null  int64
```

```
19 MonthlyRate          1470 non-null  int64
20 NumCompaniesWorked    1470 non-null  int64
21 Over18                 1470 non-null  object
22 OverTime               1470 non-null  object
23 PercentSalaryHike      1470 non-null  int64
24 PerformanceRating      1470 non-null  int64
25 RelationshipSatisfaction 1470 non-null  int64
26 StandardHours          1470 non-null  int64
27 StockOptionLevel       1470 non-null  int64
28 TotalWorkingYears      1470 non-null  int64
29 TrainingTimesLastYear  1470 non-null  int64
30 WorkLifeBalance        1470 non-null  int64
31 YearsAtCompany         1470 non-null  int64
32 YearsInCurrentRole     1470 non-null  int64
33 YearsSinceLastPromotion 1470 non-null  int64
34 YearsWithCurrManager   1470 non-null  int64
dtypes: int64(26), object(9)
memory usage: 402.1+ KB
```

```
df.corr()
```

```
<ipython-input-12-2f6f6606aa2c>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future ve
df.corr()
```

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSatisfaction	HourlyRate	JobInvolvement	JobLevel	JobSatisfaction	MonthlyIncome	MonthlyRate	NumCompaniesWorked	PercentSalaryHike	PerformanceRating	RelationshipSatisfaction	StandardHours	StockOptionLevel	TotalWorkingYears	TrainingTimesLastYear	WorkLifeBalance	YearsAtCompany	YearsInCurrentRole	YearsSinceLastPromotion	YearsWithCurrManager
Age	1.000000	0.010661	-0.001686	0.208034	NaN	-0.010145	0.010146	0.024287	0.029820	0.509604	-0.004892	0.497855	0.028051	0.299635	0.003634	0.001904	0.053535	NaN	0.037510	0.680381	-0.019621	-0.021490	0.311309	0.212901	0.216513	0.202089
DailyRate	0.010661	1.000000	-0.004985	-0.016806	NaN	-0.050990	0.018355	0.023381	0.046135	0.002966	0.030571	0.007707	-0.032182	0.038153	0.022704	0.000473	0.007846	NaN	0.042143	0.014515	0.002453	-0.037848	-0.034055	0.009932	-0.033229	-0.026363
DistanceFromHome	-0.001686	-0.004985	1.000000	0.021042	NaN	0.032916	-0.016075	0.031131	0.008783	0.005303	-0.003669	-0.017014	0.027473	-0.029251	0.040235	0.027110	0.006557	NaN	0.044872	0.004628	-0.036942	-0.026556	0.009508	0.018845	0.010029	0.014406
Education	0.208034	-0.016806	0.021042	1.000000	NaN	0.042070	-0.027128	0.016775	0.042438	0.101589	-0.011296	0.094961	-0.026084	0.126317	-0.011111	-0.024539	-0.009118	NaN	0.018422	0.148280	-0.025100	0.009819	0.069114	0.060236	0.054254	0.069065
EmployeeCount	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
EmployeeNumber	-0.010145	-0.050990	0.032916	0.042070	NaN	1.000000	0.017621	0.035179	-0.006888	-0.018519	-0.046247	-0.014829	0.012648	-0.001251	-0.012944	-0.020359	-0.069861	NaN	0.062227	-0.014365	0.023603	0.010309	-0.011240	-0.008416	-0.009019	
EnvironmentSatisfaction	0.010146	0.018355	-0.016075	-0.027128	NaN	0.017621	1.000000	-0.049857	-0.008278	0.001212	-0.006784	-0.006259	0.037600	0.012594	-0.031701	-0.029548	0.007665	NaN	0.003432	-0.002693	-0.019359	0.027627	0.001458	0.018007	0.016194	-0.004999
HourlyRate	0.024287	0.023381	0.031131	0.016775	NaN	0.035179	-0.049857	1.000000	0.029820	0.002966	0.030571	0.007707	-0.032182	0.038153	0.022704	0.000473	0.007846	NaN	0.042143	0.014515	0.002453	-0.037848	-0.034055	0.009932	-0.033229	-0.026363
JobInvolvement	0.029820	0.046135	0.008783	0.042438	NaN	-0.006888	-0.008278	0.029820	1.000000	0.002966	0.030571	0.007707	-0.032182	0.038153	0.022704	0.000473	0.007846	NaN	0.042143	0.014515	0.002453	-0.037848	-0.034055	0.009932	-0.033229	-0.026363
JobLevel	0.509604	0.002966	0.005303	0.101589	NaN	-0.018519	0.001212	0.002966	0.002966	1.000000	-0.006784	-0.006259	0.037600	0.012594	-0.031701	-0.029548	0.007665	NaN	0.003432	-0.002693	-0.019359	0.027627	0.001458	0.018007	0.016194	-0.004999
JobSatisfaction	-0.004892	0.030571	-0.003669	-0.011296	NaN	-0.046247	-0.006784	-0.006784	-0.006784	-0.006784	1.000000	-0.006259	0.037600	0.012594	-0.031701	-0.029548	0.007665	NaN	0.003432	-0.002693	-0.019359	0.027627	0.001458	0.018007	0.016194	-0.004999
MonthlyIncome	0.497855	0.007707	-0.017014	0.094961	NaN	-0.014829	-0.006259	0.007707	0.007707	0.007707	0.007707	1.000000	0.028051	0.299635	0.003634	0.001904	0.053535	NaN	0.037510	0.680381	-0.019621	-0.021490	0.311309	0.212901	0.216513	0.202089
MonthlyRate	0.028051	-0.032182	0.027473	-0.026084	NaN	0.012648	0.037600	0.028051	-0.032182	-0.032182	-0.032182	0.028051	1.000000	0.299635	0.003634	0.001904	0.053535	NaN	0.037510	0.680381	-0.019621	-0.021490	0.311309	0.212901	0.216513	0.202089
NumCompaniesWorked	0.299635	0.038153	-0.029251	0.126317	NaN	-0.001251	0.012594	-0.001251	-0.001251	-0.001251	-0.001251	0.012594	0.012594	1.000000	0.003634	0.001904	0.053535	NaN	0.037510	0.680381	-0.019621	-0.021490	0.311309	0.212901	0.216513	0.202089
PercentSalaryHike	0.003634	0.022704	0.040235	-0.011111	NaN	-0.012944	-0.031701	-0.012944	-0.012944	-0.012944	-0.012944	-0.012944	-0.012944	-0.012944	1.000000	0.001904	0.053535	NaN	0.037510	0.680381	-0.019621	-0.021490	0.311309	0.212901	0.216513	0.202089
PerformanceRating	0.001904	0.000473	0.027110	-0.024539	NaN	-0.020359	-0.029548	-0.020359	-0.020359	-0.020359	-0.020359	-0.020359	-0.020359	-0.020359	-0.020359	1.000000	0.007846	NaN	0.037510	0.680381	-0.019621	-0.021490	0.311309	0.212901	0.216513	0.202089
RelationshipSatisfaction	0.053535	0.007846	0.006557	-0.009118	NaN	-0.069861	0.007665	0.007846	0.007846	0.007846	0.007846	0.007846	0.007846	0.007846	0.007846	0.007846	0.007846	NaN	0.037510	0.680381	-0.019621	-0.021490	0.311309	0.212901	0.216513	0.202089
StandardHours	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
StockOptionLevel	0.037510	0.042143	0.044872	0.018422	NaN	0.062227	0.003432	0.042143	0.042143	0.042143	0.042143	0.042143	0.042143	0.042143	0.042143	0.042143	0.042143	NaN	1.000000	0.680381	-0.019621	-0.021490	0.311309	0.212901	0.216513	0.202089
TotalWorkingYears	0.680381	0.014515	0.004628	0.148280	NaN	-0.014365	-0.002693	0.014515	0.014515	0.014515	0.014515	0.014515	0.014515	0.014515	0.014515	0.014515	0.014515	NaN	0.680381	1.000000	-0.019621	-0.021490	0.311309	0.212901	0.216513	0.202089
TrainingTimesLastYear	-0.019621	0.002453	-0.036942	-0.025100	NaN	0.023603	-0.019359	-0.036942	-0.036942	-0.036942	-0.036942	-0.036942	-0.036942	-0.036942	-0.036942	-0.036942	-0.036942	NaN	0.023603	-0.019359	1.000000	0.027627	0.001458	0.018007	0.016194	-0.004999
WorkLifeBalance	-0.021490	-0.037848	-0.026556	0.009819	NaN	0.010309	0.027627	-0.026556	-0.026556	-0.026556	-0.026556	-0.026556	-0.026556	-0.026556	-0.026556	-0.026556	-0.026556	NaN	0.010309	0.027627	0.027627	1.000000	0.001458	0.018007	0.016194	-0.004999
YearsAtCompany	0.311309	-0.034055	0.009508	0.069114	NaN	-0.011240	0.001458	0.009508	0.009508	0.009508	0.009508	0.009508	0.009508	0.009508	0.009508	0.009508	0.009508	NaN	0.001458	0.018007	0.001458	0.001458	1.000000	0.018007	0.016194	-0.004999
YearsInCurrentRole	0.212901	0.009932	0.018845	0.060236	NaN	-0.008416	0.018007	0.018845	0.018845	0.018845	0.018845	0.018845	0.018845	0.018845	0.018845	0.018845	0.018845	NaN	0.001458	0.018007	0.001458	0.001458	0.001458	1.000000	0.016194	-0.004999
YearsSinceLastPromotion	0.216513	-0.033229	0.010029	0.054254	NaN	-0.009019	0.016194	0.054254	0.054254	0.054254	0.054254	0.054254	0.054254	0.054254	0.054254	0.054254	0.054254	NaN	0.016194	0.016194	0.016194	0.016194	0.016194	0.016194	1.000000	-0.004999
YearsWithCurrManager	0.202089	-0.026363	0.014406	0.069065	NaN	-0.009197	-0.004999	0.069065	0.069065	0.069065	0.069065	0.069065	0.069065	0.069065	0.069065	0.069065	0.069065	NaN	-0.009197	-0.004999	-0.009197	-0.009197	-0.009197	-0.009197	-0.009197	1.000000

26 rows × 26 columns

```
df.corr().MonthlyRate.sort_values(ascending=False)
```

```
<ipython-input-13-d4025e99262a>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future ve
df.corr().MonthlyRate.sort_values(ascending=False)
MonthlyRate          1.000000
JobLevel              0.039563
EnvironmentSatisfaction 0.037600
MonthlyIncome         0.034814
Age                   0.028051
DistanceFromHome      0.027473
TotalWorkingYears     0.026442
NumCompaniesWorked    0.017521
```

```

EmployeeNumber      0.012648
WorkLifeBalance      0.007963
YearsSinceLastPromotion 0.001567
TrainingTimesLastYear 0.001467
JobSatisfaction      0.000644
RelationshipSatisfaction -0.004085
PercentSalaryHike    -0.006429
PerformanceRating    -0.009811
YearsInCurrentRole   -0.012815
HourlyRate           -0.015297
JobInvolvement       -0.016322
YearsAtCompany       -0.023655
Education            -0.026084
DailyRate            -0.032182
StockOptionLevel     -0.034323
YearsWithCurrManager -0.036746
EmployeeCount        NaN
StandardHours        NaN
Name: MonthlyRate, dtype: float64

```

```
df.isnull().any()
```

```

Age                False
Attrition          False
BusinessTravel     False
DailyRate          False
Department         False
DistanceFromHome   False
Education          False
EducationField     False
EmployeeCount      False
EmployeeNumber     False
EnvironmentSatisfaction False
Gender             False
HourlyRate         False
JobInvolvement     False
JobLevel           False
JobRole           False
JobSatisfaction    False
MaritalStatus      False
MonthlyIncome      False
MonthlyRate        False
NumCompaniesWorked False
Over18            False
OverTime           False
PercentSalaryHike  False
PerformanceRating  False
RelationshipSatisfaction False
StandardHours      False
StockOptionLevel   False
TotalWorkingYears  False
TrainingTimesLastYear False
WorkLifeBalance    False
YearsAtCompany     False
YearsInCurrentRole False
YearsSinceLastPromotion False
YearsWithCurrManager False
dtype: bool

```

```
df.isnull().sum()
```

```

Age                0
Attrition          0
BusinessTravel     0
DailyRate          0
Department         0
DistanceFromHome   0
Education          0
EducationField     0
EmployeeCount      0
EmployeeNumber     0
EnvironmentSatisfaction 0
Gender             0
HourlyRate         0
JobInvolvement     0
JobLevel           0
JobRole           0
JobSatisfaction    0
MaritalStatus      0
MonthlyIncome      0
MonthlyRate        0
NumCompaniesWorked 0
Over18            0
OverTime           0
PercentSalaryHike  0
PerformanceRating  0
RelationshipSatisfaction 0

```

```
StandardHours      0
StockOptionLevel   0
TotalWorkingYears  0
TrainingTimesLastYear  0
WorkLifeBalance    0
YearsAtCompany     0
YearsInCurrentRole  0
YearsSinceLastPromotion  0
YearsWithCurrManager  0
dtype: int64
```

```
df.OverTime.nunique()
```

```
2
```

```
df.OverTime.unique()
```

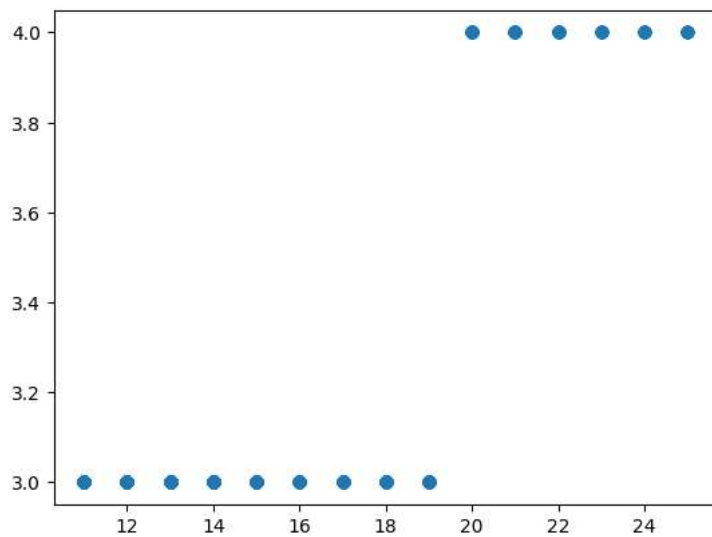
```
array(['Yes', 'No'], dtype=object)
```

```
df.OverTime.value_counts()
```

```
No      1054
Yes       416
Name: OverTime, dtype: int64
```

```
plt.scatter(df["PercentSalaryHike"],df["PerformanceRating"])
```

```
<matplotlib.collections.PathCollection at 0x7ad7238f4460>
```



```
sns.heatmap(df.corr(),annot=True)
```

```
<ipython-input-20-8df7bcac526d>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future ve
sns.heatmap(df.corr(),annot=True)
<Axes: >
```



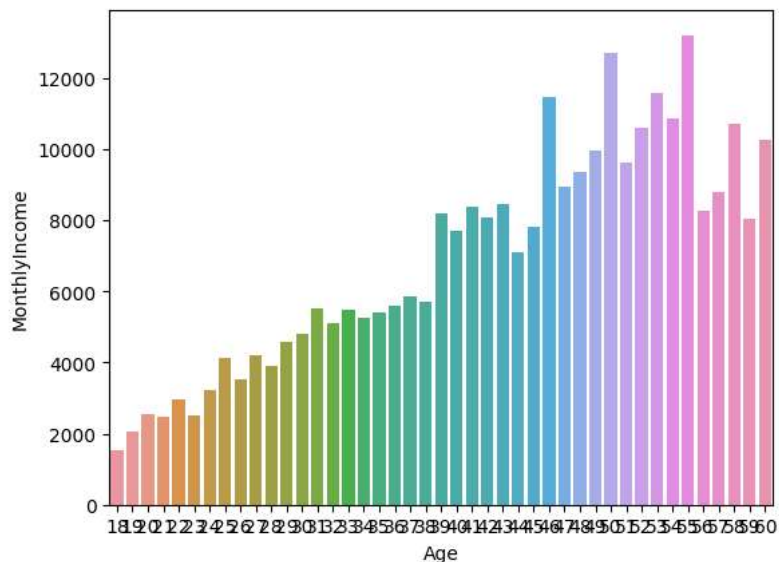
```
sns.barplot(x=df["Age"],y=df["MonthlyIncome"],ci=0)
```

```
<ipython-input-21-3cd0e332144a>:1: FutureWarning:
```

The `ci` parameter is deprecated. Use `errorbar=('ci', 0)` for the same effect.

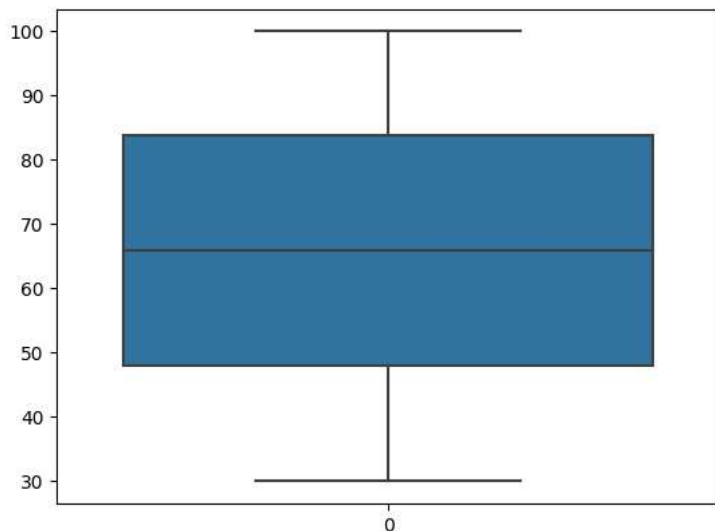
```
sns.barplot(x=df["Age"],y=df["MonthlyIncome"],ci=0)
```

```
<Axes: xlabel='Age', ylabel='MonthlyIncome'>
```

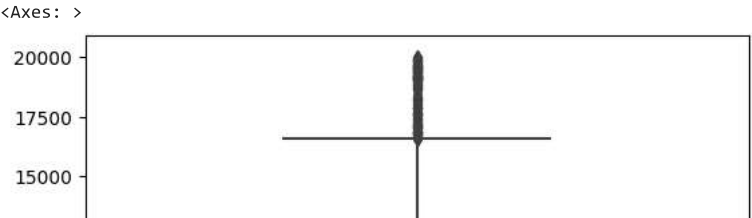


```
sns.boxplot(df["HourlyRate"])
```

```
<Axes: >
```



```
sns.boxplot(df["MonthlyIncome"])
```



```
X=df.drop(columns=["PerformanceRating"],axis=1)
X.head()
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	
1	49	No	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	Other	1	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	
4	27	No	Travel_Rarely	591	Research & Development	2	1	Medical	1	

5 rows × 34 columns

```
X.shape
```

(1470, 34)

```
type(X)
```

pandas.core.frame.DataFrame

```
y=df["PerformanceRating"]
y.head()
```

0	3
1	4
2	3
3	3
4	3

Name: PerformanceRating, dtype: int64

```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
```

```
X["MonthlyIncome"]=le.fit_transform(X["MonthlyIncome"])
```

```
X.head()
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	
1	49	No	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	Other	1	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	
4	27	No	Travel_Rarely	591	Research & Development	2	1	Medical	1	

5 rows × 34 columns

```
print(le.classes_)
```

[1009 1051 1052 ... 19943 19973 19999]

```
mapping=dict(zip(le.classes_,range(len(le.classes_))))
```

```
mapping
```

```
7484: 943,  
7491: 944,  
7510: 945,  
7525: 946,  
7547: 947,  
7553: 948,  
7587: 949,  
7596: 950,  
7625: 951,  
7632: 952,  
7637: 953,  
7639: 954,  
7642: 955,  
7644: 956,  
7654: 957,  
7655: 958,  
7725: 959,  
7756: 960,  
7779: 961,  
7823: 962,  
7847: 963,  
7861: 964,  
7879: 965,  
7880: 966,  
7898: 967,  
7918: 968,  
7945: 969,  
7969: 970,  
7978: 971,  
7988: 972,  
7991: 973,  
8008: 974,  
8020: 975,  
8095: 976,  
8103: 977,  
8120: 978,  
8161: 979,  
8189: 980,  
8224: 981,  
8237: 982,  
8268: 983,  
8321: 984,  
8346: 985,  
8376: 986,  
8380: 987,  
8381: 988,  
8392: 989,  
8396: 990,  
8412: 991,  
8446: 992,  
8463: 993,  
8474: 994,  
8500: 995,  
8564: 996,  
8578: 997,  
8606: 998,  
8620: 999,  
...}
```

```
X =df.drop(['Attrition','BusinessTravel','EducationField','OverTime'],axis=1) # Features  
y =df['Attrition']
```

```
X['Department'] = preprocessing.LabelEncoder().fit_transform(X['Department'])  
X['Education'] = preprocessing.LabelEncoder().fit_transform(X['Education'])  
X['JobRole'] = preprocessing.LabelEncoder().fit_transform(X['JobRole'])  
X['Gender'] = preprocessing.LabelEncoder().fit_transform(X['Gender'])  
X['MaritalStatus'] = preprocessing.LabelEncoder().fit_transform(X['MaritalStatus'])  
X['Over18'] = preprocessing.LabelEncoder().fit_transform(X['Over18'])
```

```
Scaler = StandardScaler()  
X = Scaler.fit_transform(X)
```

```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.2, random_state = 2)
```

```
print(X.shape)  
print(X_train.shape)  
print(X_test.shape)
```

```
(1470, 31)
(1176, 31)
(294, 31)
```

```
from sklearn.linear_model import LogisticRegression
model=LogisticRegression()
```

```
models = [] # ML Models
models.append(("Random Forest", RandomForestClassifier()))
models.append(("Logistic Regression", LogisticRegression(solver='liblinear')))
models.append(("SVM", svm.SVC(kernel='linear')))
```

```
n_folds = 5
results = []
for name, model in models:
    kfold = model_selection.KFold(n_splits=n_folds)
    print("Testing model:", name)
```

```
# Cross Validation Score
cv_results = model_selection.cross_val_score(model, X_train, y_train, cv=kfold, scoring="f1_weighted", verbose=0, n_jobs=-1)
```

```
# Fitting the Model
model.fit(X_train,y_train)
```

```
# Model Predictions and Finding Accuracy
train_pred = model.predict(X_train)
Training_score = accuracy_score(train_pred,y_train)
test_pred = model.predict(X_test)
Test_score = accuracy_score(test_pred,y_test)
```

```
results.append(cv_results)
```

```
msg = f"Cross_Val Mean: {cv_results.mean()}, Training Accuracy: {Training_score}, Testing Accuracy: {Test_score}"
print(msg + "\n")
```

```
Testing model: Random Forest
Cross_Val Mean: 0.7974876748112971, Training Accuracy: 1.0, Testing Accuracy: 0.8469387755102041
```

```
Testing model: Logistic Regression
Cross_Val Mean: 0.8219775205615518, Training Accuracy: 0.8656462585034014, Testing Accuracy: 0.8571428571428571
```

```
Testing model: SVM
Cross_Val Mean: 0.7660141990060427, Training Accuracy: 0.8392857142857143, Testing Accuracy: 0.8367346938775511
```

```
from sklearn.metrics import accuracy_score,classification_report
```

```
accuracy_score(test_pred,y_test)
```

```
0.8367346938775511
```

```
print(classification_report(y_test,test_pred))
```

	precision	recall	f1-score	support
No	0.84	1.00	0.91	246
Yes	0.00	0.00	0.00	48
accuracy			0.84	294
macro avg	0.42	0.50	0.46	294
weighted avg	0.70	0.84	0.76	294

```
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are
_warn_prf(average, modifier, msg_start, len(result))
```

```
pd.crosstab(y_test,test_pred)
```