▼ ASSIGNMENT-4 Sept 22

1.Download the Employee Attrition Dataset https://www.kaggle.com/datasets/patelprashant/employee-attrition

2.Perform Data Preprocessing

3. Model Building using Logistic Regression and Decision Tree and Random Forest

4. Calculate Performance metrics

Data Preprocessing.

- o Import the Libraries.
- o Importing the dataset.
- o Checking for Null Values.
- o Data Visualization.o Outlier Detection
- o Splitting Dependent and Independent variables
- o- Encoding
- o Feature Scaling.
- o Splitting Data into Train and Test.

#Import the Libraries.
import numpy as np

import pandas as pd
import matplotlib.pyplot as plt

import seaborn as sns

#Importing the dataset.
df=pd.read_csv("/content/WA_Fn-UseC_-HR-Employee-Attrition.csv")

df.head()

	Age	Attriti	on I	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber	 . RelationshipSatisfaction	StandardHours	StockOptionLevel	TotalWorkingYears	TrainingTimesLastYear	WorkLifeBalance	YearsAtCompany	YearsInCurrent
(0 41	١	'es	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	1	 . 1	80	0	8	0	1	6	
	1 49		No T	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	2	 . 4	80	1	10	3	3	10	
2	2 37	١	'es	Travel_Rarely	1373	Research & Development	2	2	Other	1	4	 . 2	80	0	7	3	3	0	
;	3 33		No T	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	5	 . 3	80	0	8	3	3	8	
4	4 27		No	Travel_Rarely	591	Research & Development	2	1	Medical	1	7	 . 4	80	1	6	3	3	2	
5	rows ×	35 column	ıs																

df.shape

(1470, 35)

df.StockOptionLevel.value_counts()

- 0 631
- 1 596
- 2 158 3 85
- Name: StockOptionLevel, dtype: int64

df.EmployeeCount.value_counts()

1 1470

Name: EmployeeCount, dtype: int64

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469

Data columns (total 35 columns): Non-Null Count Dtype # Column 0 Age 1470 non-null int64 1 Attrition 1470 non-null object BusinessTravel 1470 non-null object 1470 non-null int64 3 DailyRate 4 Department5 DistanceFromHome 1470 non-null object 1470 non-null int64 1470 non-null int64 1470 non-null object 1470 non-null int64 Education EducationField EmployeeCount EmployeeNumber 1470 non-null int64 EnvironmentSatisfaction 1470 non-null int64 11 Gender 1470 non-null object 12 HourlyRate 1470 non-null int64 13 JobInvolvement 1470 non-null int64 14 JobLevel15 JobRole 1470 non-null int64 1470 non-null object 1470 non-null int64 16 JobSatisfaction 17 MaritalStatus 1470 non-null object 1470 non-null int64 18 MonthlyIncome 19 MonthlyRate 1470 non-null int64 1470 non-null int64 20 NumCompaniesWorked 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 1470 non-null int64 27 StockOptionLevel 1470 non-null int64 28 TotalWorkingYears 29 TrainingTimesLastYear 1470 non-null int64 1470 non-null int64 30 WorkLifeBalance 31 YearsAtCompany 1470 non-null int64 32 YearsInCurrentRole 1470 non-null int64 33 YearsSinceLastPromotion 1470 non-null int64 dtypes: int64(26), object(9) memory usage: 402.1+ KB

df.describe()

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSatisfaction	HourlyRate	JobInvolvement	JobLevel	Re	elationshipSatisfaction	StandardHours	StockOptionLevel	TotalWorkingYears	TrainingTimesLastYear	WorkLifeBalance	Years
count	1470.000000	1470.000000	1470.000000	1470.000000	1470.0	1470.000000	1470.000000	1470.000000	1470.000000	1470.000000		1470.000000	1470.0	1470.000000	1470.000000	1470.000000	1470.000000	14
mean	36.923810	802.485714	9.192517	2.912925	1.0	1024.865306	2.721769	65.891156	2.729932	2.063946		2.712245	80.0	0.793878	11.279592	2.799320	2.761224	
std	9.135373	403.509100	8.106864	1.024165	0.0	602.024335	1.093082	20.329428	0.711561	1.106940		1.081209	0.0	0.852077	7.780782	1.289271	0.706476	
min	18.000000	102.000000	1.000000	1.000000	1.0	1.000000	1.000000	30.000000	1.000000	1.000000		1.000000	80.0	0.000000	0.000000	0.000000	1.000000	
25%	30.000000	465.000000	2.000000	2.000000	1.0	491.250000	2.000000	48.000000	2.000000	1.000000		2.000000	80.0	0.000000	6.000000	2.000000	2.000000	
50%	36.000000	802.000000	7.000000	3.000000	1.0	1020.500000	3.000000	66.000000	3.000000	2.000000		3.000000	80.0	1.000000	10.000000	3.000000	3.000000	
75%	43.000000	1157.000000	14.000000	4.000000	1.0	1555.750000	4.000000	83.750000	3.000000	3.000000		4.000000	80.0	1.000000	15.000000	3.000000	3.000000	
max	60.000000	1499.000000	29.000000	5.000000	1.0	2068.000000	4.000000	100.000000	4.000000	5.000000		4.000000	80.0	3.000000	40.000000	6.000000	4.000000	
8 rows ×	26 columns																	

#Checking for Null Values. 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

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TotalWorkingYears False
TrainingTimesLastYear False
WorkLifeBalance False
YearsAtCompany False
YearsInCurrentRole False
YearsSinceLastPromotion False
YearsWithCurrManager False
dtype: bool

df.isnull().sum()

Age Attrition BusinessTravel DailyRate Department DistanceFromHome Education EducationField EmployeeCount EmployeeNumber EnvironmentSatisfaction Gender HourlyRate JobInvolvement JobLevel JobRole JobSatisfaction MaritalStatus MonthlyIncome MonthlyRate NumCompaniesWorked Over18 OverTime PercentSalaryHike PerformanceRating RelationshipSatisfaction StandardHours StockOptionLevel TotalWorkingYears
TrainingTimesLastYear
WorkLifeBalance
YearsAtCompany
YearsInCurrentRole YearsSinceLastPromotion YearsWithCurrManager dtype: int64

#Data Visualization. sns.histplot(df["Age"])

<Axes: xlabel='Age', ylabel='Count'>

#Data Visualization. sns.displot(df["DailyRate"])

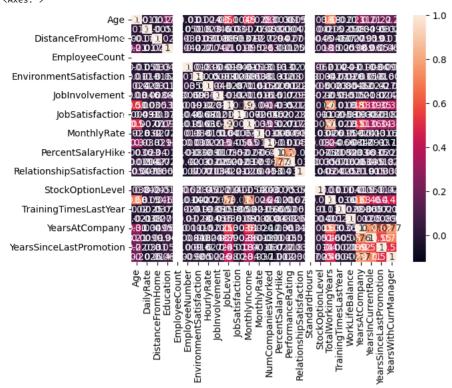
df.corr()

<ipython-input-16-2f6f6606aa2c>: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.
df.corr()

df.corr()			0					,				,	,			,	
	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSatisfaction	HourlyRate	JobInvolvement	JobLevel	1	RelationshipSatisfaction	StandardHours	StockOptionLevel	TotalWorkingYears	TrainingTimesLastYear	WorkLifeBala
Age	1.000000	0.010661	-0.001686	0.208034	NaN	-0.010145	0.010146	0.024287	0.029820	0.509604		0.053535	NaN	0.037510	0.680381	-0.019621	-0.021
DailyRate	0.010661	1.000000	-0.004985	-0.016806	NaN	-0.050990	0.018355	0.023381	0.046135	0.002966		0.007846	NaN	0.042143	0.014515	0.002453	-0.037
DistanceFromHome	-0.001686	-0.004985	1.000000	0.021042	NaN	0.032916	-0.016075	0.031131	0.008783	0.005303		0.006557	NaN	0.044872	0.004628	-0.036942	-0.026
Education	0.208034	-0.016806	0.021042	1.000000	NaN	0.042070	-0.027128	0.016775	0.042438	0.101589		-0.009118	NaN	0.018422	0.148280	-0.025100	0.009
EmployeeCount	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN		NaN	NaN	NaN	NaN	NaN	N
EmployeeNumber	-0.010145	-0.050990	0.032916	0.042070	NaN	1.000000	0.017621	0.035179	-0.006888	-0.018519		-0.069861	NaN	0.062227	-0.014365	0.023603	0.010
EnvironmentSatisfaction	0.010146	0.018355	-0.016075	-0.027128	NaN	0.017621	1.000000	-0.049857	-0.008278	0.001212		0.007665	NaN	0.003432	-0.002693	-0.019359	0.027
HourlyRate	0.024287	0.023381	0.031131	0.016775	NaN	0.035179	-0.049857	1.000000	0.042861	-0.027853		0.001330	NaN	0.050263	-0.002334	-0.008548	-0.004
JobInvolvement	0.029820	0.046135	0.008783	0.042438	NaN	-0.006888	-0.008278	0.042861	1.000000	-0.012630		0.034297	NaN	0.021523	-0.005533	-0.015338	-0.014
JobLevel	0.509604	0.002966	0.005303	0.101589	NaN	-0.018519	0.001212	-0.027853	-0.012630	1.000000		0.021642	NaN	0.013984	0.782208	-0.018191	0.037
JobSatisfaction	-0.004892	0.030571	-0.003669	-0.011296	NaN	-0.046247	-0.006784	-0.071335	-0.021476	-0.001944		-0.012454	NaN	0.010690	-0.020185	-0.005779	-0.019
MonthlyIncome	0.497855	0.007707	-0.017014	0.094961	NaN	-0.014829	-0.006259	-0.015794	-0.015271	0.950300		0.025873	NaN	0.005408	0.772893	-0.021736	0.030
MonthlyRate	0.028051	-0.032182	0.027473	-0.026084	NaN	0.012648	0.037600	-0.015297	-0.016322	0.039563		-0.004085	NaN	-0.034323	0.026442	0.001467	0.007
NumCompaniesWorked	0.299635	0.038153	-0.029251	0.126317	NaN	-0.001251	0.012594	0.022157	0.015012	0.142501		0.052733	NaN	0.030075	0.237639	-0.066054	-0.008
PercentSalaryHike	0.003634	0.022704	0.040235	-0.011111	NaN	-0.012944	-0.031701	-0.009062	-0.017205	-0.034730		-0.040490	NaN	0.007528	-0.020608	-0.005221	-0.003
PerformanceRating	0.001904	0.000473	0.027110	-0.024539	NaN	-0.020359	-0.029548	-0.002172	-0.029071	-0.021222		-0.031351	NaN	0.003506	0.006744	-0.015579	0.002
RelationshipSatisfaction	0.053535	0.007846	0.006557	-0.009118	NaN	-0.069861	0.007665	0.001330	0.034297	0.021642		1.000000	NaN	-0.045952	0.024054	0.002497	0.019
StandardHours	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN		NaN	NaN	NaN	NaN	NaN	N
StockOptionLevel	0.037510	0.042143	0.044872	0.018422	NaN	0.062227	0.003432	0.050263	0.021523	0.013984		-0.045952	NaN	1.000000	0.010136	0.011274	0.004
TotalWorkingYears	0.680381	0.014515	0.004628	0.148280	NaN	-0.014365	-0.002693	-0.002334	-0.005533	0.782208		0.024054	NaN	0.010136	1.000000	-0.035662	0.001
TrainingTimesLastYear	-0.019621	0.002453	-0.036942	-0.025100	NaN	0.023603	-0.019359	-0.008548	-0.015338	-0.018191		0.002497	NaN	0.011274	-0.035662	1.000000	0.028
WorkLifeBalance	-0.021490	-0.037848	-0.026556	0.009819	NaN	0.010309	0.027627	-0.004607	-0.014617	0.037818		0.019604	NaN	0.004129	0.001008	0.028072	1.000
YearsAtCompany	0.311309	-0.034055	0.009508	0.069114	NaN	-0.011240	0.001458	-0.019582	-0.021355	0.534739		0.019367	NaN	0.015058	0.628133	0.003569	0.012
YearsInCurrentRole	0.212901	0.009932	0.018845	0.060236	NaN	-0.008416	0.018007	-0.024106	0.008717	0.389447		-0.015123	NaN	0.050818	0.460365	-0.005738	0.049
YearsSinceLastPromotion	0.216513	-0.033229	0.010029	0.054254	NaN	-0.009019	0.016194	-0.026716	-0.024184	0.353885		0.033493	NaN	0.014352	0.404858	-0.002067	0.008
YearsWithCurrManager	0.202089	-0.026363	0.014406	0.069065	NaN	-0.009197	-0.004999	-0.020123	0.025976	0.375281		-0.000867	NaN	0.024698	0.459188	-0.004096	0.002
26 rows × 26 columns																	

Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber	٠	${\tt RelationshipSatisfaction}$	StandardHours	StockOptionLevel	TotalWorkingYears	TrainingTimesLastYear	WorkLifeBalance	YearsAtCompany	YearsInCurren
0 41	Yes	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	1		1	80	0	8	0	1	6	
1 49	No	Travel_Frequently	279	Research & Development	8	3 1	Life Sciences	1	2	2	4	80	1	10	3	3	10	

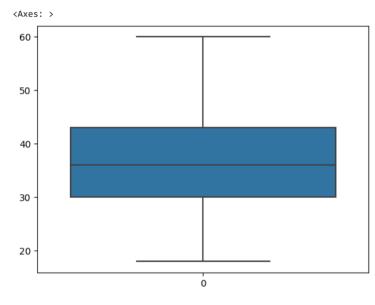
numeric_columns = df.select_dtypes(include='number').columns
sns.heatmap(df[numeric_columns].corr(), annot=True)



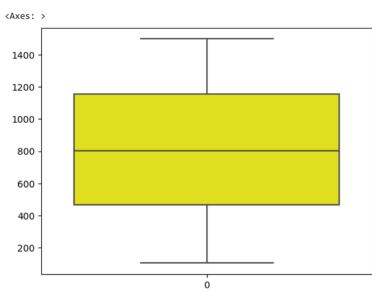
$\verb|sns.heatmap(df.corr(numeric_only=True), annot=True)|\\$



sns.boxplot(df['Age'])



sns.boxplot(df['DailyRate'],color='yellow')



591

#Splitting Dependent and Independent variables
x=df.iloc[:,1:4]
x.head()

Attrition	BusinessTravel	DailyRate	
Yes	Travel_Rarely	1102	ılı
No	Travel_Frequently	279	
Yes	Travel_Rarely	1373	
No	Travel_Frequently	1392	
	Yes No Yes	Yes Travel_Rarely No Travel_Frequently Yes Travel_Rarely	Yes Travel_Rarely 1102 No Travel_Frequently 279 Yes Travel_Rarely 1373

x=df.iloc[:,[i for i in range(df.shape[1]) if i!=1]]
x.head()

Travel_Rarely

Age	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber	r EnvironmentSatisfaction	Relat	tionshipSatisfaction Stand	dardHours Sto	ockOptionLevel	TotalWorkingYears	TrainingTimesLastYear	WorkLifeBalance	YearsAtCompany
0 41	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	1	1 2		1	80	0	8	0	1	6
1 49	Travel_Frequently	279	Research & Development		1	Life Sciences	1	2	2 3		4	80	1	10	3	3	10
2 37	Travel_Rarely	1373	Research & Development		2	Other	1	4	4		2	80	0	7	3	3	0
3 33	Travel_Frequently	1392	Research & Development		4	Life Sciences	1	5	5 4		3	80	0	8	3	3	8
4 27	Travel_Rarely	591	Research & Development		1	Medical	1	7	7 1		4	80	1	6	3	3	2
5 rows ×	34 columns																



##LabelEncoding

from sklearn.preprocessing import LabelEncoder

le=LabelEncoder() a=['Age','Department','EducationField','BusinessTravel','Gender','JobRole','MaritalStatus','Over18','OverTime']

for i in a: $x[i]=le.fit_transform(x[i])$

iry using .loc[row_indexer,coi_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy x[i]=le.fit_transform(x[i])
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy x[i]=le.fit_transform(x[i])
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
x[i]=le.fit_transform(x[i])
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
x[i]=le.fit_transform(x[i])
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x[i]=le.fit_transform(x[i])
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x[i]=le.fit_transform(x[i])
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https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-copy
h

See the caveats in the documentation: https://pandas.pydata.org/pandas.pydata.org/pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

 $x[i]=le.fit_transform(x[i])$

<ipython-input-25-c1e99d50f975>:6: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: $\underline{\text{https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html\#returning-a-view-versus-a-copy}$ x[i]=le.fit_transform(x[i])
<ipython-input-25-c1e99d50f975>:6: SettingWithCopyWarning:

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x[i]=le.fit_transform(x[i])
<ipython-input-25-c1e99d50f975>:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
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<ipython-input-25-c1e99d50f975>:6: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame. Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: $\underline{ \text{https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html\#returning-a-view-versus-a-copy}$ x[i]=le.fit_transform(x[i])

	Age	Department	EducationField	BusinessTravel	Gender	JobRole	MaritalStatus	Over18	OverTime
0	23	2	1	2	0	7	2	0	1
1	31	1	1	1	1	6	1	0	0
2	19	1	4	2	1	2	2	0	1
3	15	1	1	1	0	6	1	0	1
4	9	1	3	2	1	2	1	0	0
1465	18	1	3	1	1	2	1	0	0
1466	21	1	3	2	1	0	1	0	0
1467	9	1	1	2	1	4	1	0	1
1468	31	2	3	1	1	7	1	0	0
1469	16	1	3	2	1	2	1	0	0

1470 rows × 9 columns

y['Attrition']=le.fit_transform(y['Attrition'])

y.head()

Att	rition	E
0	1	
1	0	
2	1	
3	0	
4	0	

#feature scaling

 ${\it from \ sklearn.preprocessing \ import \ MinMaxScaler}$

ms=MinMaxScaler()

x_scaled=pd.DataFrame(ms.fit_transform(x),columns=x.columns)

x_scaled

	Age BusinessTra	vel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber	EnvironmentSatisfaction	•••	RelationshipSatisfaction	StandardHours	StockOptionLevel	TotalWorkingYears	TrainingTimesLastYear	WorkLifeBalance	YearsAtCo
0 0.547	7619	1.0	0.715820	1.0	0.000000	0.25	0.2	0.0	0.000000	0.333333		0.000000	0.0	0.000000	0.200	0.000000	0.000000	
1 0.738	8095	0.5	0.126700	0.5	0.250000	0.00	0.2	0.0	0.000484	0.666667		1.000000	0.0	0.333333	0.250	0.500000	0.666667	
2 0.452	2381	1.0	0.909807	0.5	0.035714	0.25	0.8	0.0	0.001451	1.000000		0.333333	0.0	0.000000	0.175	0.500000	0.666667	
3 0.357	143	0.5	0.923407	0.5	0.071429	0.75	0.2	0.0	0.001935	1.000000		0.666667	0.0	0.000000	0.200	0.500000	0.666667	
4 0.214	1286	1.0	0.350036	0.5	0.035714	0.00	0.6	0.0	0.002903	0.000000		1.000000	0.0	0.333333	0.150	0.500000	0.666667	
1465 0.428	3571	0.5	0.559771	0.5	0.785714	0.25	0.6	0.0	0.996613	0.666667		0.666667	0.0	0.333333	0.425	0.500000	0.666667	
1466 0.500	0000	1.0	0.365784	0.5	0.178571	0.00	0.6	0.0	0.997097	1.000000		0.000000	0.0	0.333333	0.225	0.833333	0.666667	
1467 0.214	1286	1.0	0.037938	0.5	0.107143	0.50	0.2	0.0	0.998065	0.333333		0.333333	0.0	0.333333	0.150	0.000000	0.666667	
1468 0.738	3095	0.5	0.659270	1.0	0.035714	0.50	0.6	0.0	0.998549	1.000000		1.000000	0.0	0.000000	0.425	0.500000	0.333333	
1469 0.380	952	1.0	0.376521	0.5	0.250000	0.50	0.6	0.0	1.000000	0.333333		0.000000	0.0	0.000000	0.150	0.500000	1.000000	
1470 rows × 3	34 columns																	

#Splitting data into train and test data from sklearn.model_selection import train_test_split

x_train,x_test,y_train,y_test=train_test_split(x_scaled,y,test_size=0.3)

 ${\tt x_train.shape,x_test.shape,y_train.shape,y_test.shape}$

((1029, 34), (441, 34), (1029, 1), (441, 1))

x_train.head()

	Ag	e BusinessT	ravel [DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber	${\tt EnvironmentSatisfaction}$	• • •	${\tt RelationshipSatisfaction}$	StandardHours	StockOptionLevel	TotalWorkingYears	TrainingTimesLastYear	WorkLifeBalance	YearsAtCo
694	0.35714	3	1.0	0.692198	0.5	0.000000	0.50	0.2	0.0	0.468312	0.333333		0.000000	0.0	0.000000	0.150	0.500000	0.666667	
1057	0.26190	5	0.5	0.009306	1.0	0.428571	0.50	1.0	0.0	0.718916	0.000000		0.000000	0.0	0.000000	0.175	0.666667	0.000000	
1156	0.52381	0	1.0	0.559771	0.5	0.500000	0.50	0.2	0.0	0.787131	0.000000		1.000000	0.0	0.666667	0.450	0.333333	0.666667	
798	0.35714	3	1.0	0.654975	0.5	0.857143	0.50	0.6	0.0	0.535559	0.000000		0.333333	0.0	0.000000	0.125	0.000000	0.666667	
1451	0.47619	00	1.0	0.173944	1.0	0.321429	0.25	0.2	0.0	0.986938	0.000000		0.666667	0.0	0.333333	0.250	0.166667	0.666667	
5 rows	34 colu	mns																	

Model Building

- Import the model building Libraries
- o Initializing the model o Training and testing the model

```
9/28/23, 9:55 PM
```

o Evaluation of Model o Save the Model

from sklearn.linear_model import LogisticRegression model=LogisticRegression()

model.fit(x_train,y_train)

/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:1143: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,), for example using ravel().

▼ LogisticRegression

LogisticRegression()

pred=model.predict(x_test)

pred

```
0,\ 0,\ 0,\ 0,\ 0,\ 0,\ 0,\ 0,\ 1,\ 0,\ 0,\ 0,\ 0,\ 0,\ 0,\ 0,\ 0,\ 0,\ 1,\ 0,
 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0,
 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
```

y_test

	Attrition	
1415	0	th
1073	0	
54	0	
348	0	
953	1	
320	0	
183	0	
1219	0	
1283	0	
1164	0	
441 rov	ws × 1 columns	

#Evaluation of Model

 $from \ sklearn. metrics \ import \ accuracy_score, confusion_matrix, classification_report, roc_auc_score, roc_curve$ accuracy_score(y_test,pred)

0.8639455782312925

confusion_matrix(y_test,pred)

array([[360, 13], [47, 21]])

print(pred.shape)

(441, 1)(441,)

print(y_test.shape)

print(classification_report(y_test,pred))

	precision	recall	f1-score	support
0	0.88	0.97	0.92	373
1	0.62	0.31	0.41	68
accuracy			0.86	441
macro avg	0.75	0.64	0.67	441
weighted avg	0.84	0.86	0.84	441

Random Forest and Decision Tree

 $from \ sklearn. metrics \ import \ accuracy_score, confusion_matrix, classification_report, roc_auc_score, roc_curve$

accuracy_score(y_test,pred)

0.8639455782312925

d_y_predict = model1.predict(x_test)

from sklearn.tree import DecisionTreeClassifier model1 = DecisionTreeClassifier(max_depth=4,splitter='best',criterion='entropy') model1.fit(x_train,y_train)

d_y_predict

```
1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
  0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0,
  0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
  0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
  0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
```

#Evaluating Metrics- Decision Tree

 $from \ sklearn.metrics \ import \ accuracy_score, classification_report, confusion_matrix$ print('Testing Accuracy = ', accuracy_score(y_test,d_y_predict))

Testing Accuracy = 0.8344671201814059

confusion_matrix(y_test,d_y_predict)

array([[359, 14], [59, 9]])

print(classification_report(y_test,d_y_predict))

	precision	recall	f1-score	support
0 1	0.86 0.39	0.96 0.13	0.91 0.20	373 68
accuracy macro avg weighted avg	0.63 0.79	0.55 0.83	0.83 0.55 0.80	441 441 441

 $from \ sklearn.ensemble \ import \ Random Forest Classifier$ rfc=RandomForestClassifier()

 $forest_params = [\{'max_depth': list(range(10, 15)), 'max_features': list(range(0, 14))\}]$

from sklearn.model_selection import GridSearchCV

parameter={

```
'criterion':['gini','entropy'],
'splitter':['best','random'],
'max_depth':[1,2,3,4,5],
   'max_features':['auto', 'sqrt', 'log2']
rfc_cv= GridSearchCV(rfc,param_grid=forest_params,cv=10,scoring="accuracy")
from sklearn.ensemble import RandomForestClassifier
model2 =RandomForestClassifier(criterion='entropy')
model2.fit(x\_train,y\_train)
      <ipython-input-53-8761b0c09731>:3: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,), for example using ravel().
        model2.fit(x_train,y_train)
                    {\tt RandomForestClassifier}
       RandomForestClassifier(criterion='entropy')
r_y_predict = model2.predict(x_test)
r_y_predict_train = model2.predict(x_train)
print('Testing Accuracy = ', accuracy_score(y_test,r_y_predict))
print('Training Accuracy = ', accuracy_score(y_train,r_y_predict_train))
      Testing Accuracy = 0.8684807256235828
Training Accuracy = 1.0
print(classification_report(y_test,r_y_predict))
                       precision recall f1-score support
                            0.87
                                                                 373
                   0
                                        0.99
                                                    0.93
                            0.86
                                        0.18
                                                                 68
                                                    0.29
                                                    0.87
                                                                 441
           accuracy
      macro avg
weighted avg
                            0.86
0.87
                                                    0.61
0.83
                                                                 441
441
                                        0.59
                                        0.87
confusion_matrix(y_test,r_y_predict)
      array([[371, 2],
[ 56, 12]])
```