

Project Title:- IBM HR Analytics Employee Attrition & Performance

Tools:- Python,DAX(PowerQuery),Jupyternotebook,SQL

Domain:- Data Analyst & Data scientist

Data Set:- Data Folder -- Contains Raw Data Files (Data can be downloaded from [kaggle](#))

Objective: This real-world HR analytics project focused on understanding employee attrition trends and identifying key factors influencing turnover using data-driven insights. With 35 HR variables across 1,470 employees, the analysis helped HR professionals pinpoint critical retention levers and proactively improve employee experience.

INTRODUCTION

Understanding the data:

- **The data is taken from the source** [kaggle](#)
- The data contains 1 csv file HR-Employee-Attrition.CSV

Tasks:

- **Data Cleaning:** Clean the Attrition Dataset by handling missing values,duplicates and inconsstencies.
- **Data Aggregaton:** Aggregate the data to compute Attrition count,Attrition Rate,Active Employees and Measure like performance rating label,job satisfaction level,work life balance label,Job Involvement level,Environment Satisfaction level.
- **Visualization of Dashboard:** Create various Visualization such as:
 1. EducationField & Jobrole by Department Count(clustered bar chart)
 2. Gender(slicer)
 3. MaritalStatus by Sum of Attrition & Relationship Education (clustered bar chart)
 4. Attrition by JobRole(clustered bar chart)
 5. Distance from home & Education field by Jobrole & Active employee(Ribbon Chart)
 6. Avg of Job Involvement by Education Field (Funnel)
- **Visualization For Uncover The Factor Leading to Attrition:**
 1. Monthly Income & Attrition By Education(line & clustered coloumn chart)
 2. Performance rating label,Job satisfaction,Work life balance of employee,relationship satisfaction,environment satisfaction(matrix)
 3. Avg salary hike & hourly rate by performance rating
- Build an interactive dashboard that allows users to filter by time Attrition of employee,worklife balance, performance,satisfaction etc.
- **Insights:**
 1. Accurately identify 16.12% customers (237) likely to churn

2. Highest attrition from Jobrole are of Laboratory Technician(62),Sales Executive(57),Research Scientist(47)
3. Thier Average Life balance is from 2.72 to 2.89 & Age 30 - 36
4. Stock Options of Department Research & Development(133),Sales(92) and Human Resource(12)

- **Tools:**

1. **Power BI** for dashboarding
2. **Python (Pandas, Seaborn, scikit-learn)** for ML and EDA
3. **SQL Server / CSV** as data source
4. **Jupyter Notebook** for workflow and documentation

- **ASK:** By this project, I am trying to analyse Attrition performance for **Facotors leading to Employee Attrtition** company and present my insights in a comprehensive dashboard

- **PREPARE :**

1. Load the datasets to Google Sheets and PowerQuery (SQL)
2. Prepared a copy of the dataset for further reference
3. Saved the datasets by using naming conventions in a separate file folder for easy access

- **Process :**

Importing libraries

import numpy as np # Its used primarily for numerical computing.It support for multidimensional arrays and matrices

import matplotlib.pyplot as plt # creating visualization

import seaborn as sns #Its used for statistical graphics

import pandas as pd #used for data manipulation,cleaning and Analysis

Import Data

```
data = pd.read_csv(r"C:\Users\kanak\Desktop\UNIFIED MENTOR
PROJDAproj_1IN\WA_Fn-UseC_-HR-Employee-Attrition.csv")
```

```
data.head()
```

```
data.shape
```

```
(1470, 35)
```

```
import pandas as pd
```

```
print(f'Number of duplicated data: {data.duplicated().sum()}')
```

```
print(data.isnull().sum() / len(data)*100)
```

Number of duplicated data: 0

Age 0.0

Attrition 0.0

```

BusinessTravel      0.0
DailyRate           0.0
Department          0.0
DistanceFromHome    0.0
Education           0.0
EducationField      0.0
EmployeeCount       0.0
EmployeeNumber      0.0
EnvironmentSatisfaction  0.0
Gender              0.0
HourlyRate          0.0
JobInvolvement      0.0
JobLevel            0.0
JobRole             0.0
JobSatisfaction     0.0
MaritalStatus       0.0
MonthlyIncome       0.0
MonthlyRate         0.0
NumCompaniesWorked  0.0
Over18              0.0
OverTime            0.0
PercentSalaryHike   0.0
PerformanceRating   0.0
RelationshipSatisfaction  0.0
StandardHours       0.0
StockOptionLevel    0.0
TotalWorkingYears   0.0
TrainingTimesLastYear  0.0
WorkLifeBalance     0.0
YearsAtCompany      0.0
YearsInCurrentRole  0.0
YearsSinceLastPromotion  0.0
YearsWithCurrManager  0.0

```

```
dtype: float64
```

```
data.dtypes
```

```
data.describe
```

```

<bound method NDFrame.describe of      Age Attrition  BusinessTravel  DailyRate
Department \
0    41    Yes    Travel_Rarely    1102          Sales

```

1	49	No	Travel_Frequently	279	Research & Development
2	37	Yes	Travel_Rarely	1373	Research & Development
3	33	No	Travel_Frequently	1392	Research & Development
4	27	No	Travel_Rarely	591	Research & Development
...
1465	36	No	Travel_Frequently	884	Research & Development
1466	39	No	Travel_Rarely	613	Research & Development
1467	27	No	Travel_Rarely	155	Research & Development
1468	49	No	Travel_Frequently	1023	Sales
1469	34	No	Travel_Rarely	628	Research & Development

	DistanceFromHome	Education	EducationField	EmployeeCount \
0	1	2	Life Sciences	1
1	8	1	Life Sciences	1
2	2	2	Other	1
3	3	4	Life Sciences	1
4	2	1	Medical	1
...
1465	23	2	Medical	1
1466	6	1	Medical	1
1467	4	3	Life Sciences	1
1468	2	3	Medical	1
1469	8	3	Medical	1

	EmployeeNumber	...	RelationshipSatisfaction	StandardHours \
0	1	...	1	80
1	2	...	4	80
2	4	...	2	80
3	5	...	3	80
4	7	...	4	80
...
1465	2061	...	3	80
1466	2062	...	1	80
1467	2064	...	2	80
1468	2065	...	4	80
1469	2068	...	1	80

	StockOptionLevel	TotalWorkingYears	TrainingTimesLastYear \
0	0	8	0

1	1	10	3
2	0	7	3
3	0	8	3
4	1	6	3
...
1465	1	17	3
1466	1	9	5
1467	1	6	0
1468	0	17	3
1469	0	6	3

	WorkLifeBalance	YearsAtCompany	YearsInCurrentRole \
0	1	6	4
1	3	10	7
2	3	0	0
3	3	8	7
4	3	2	2
...
1465	3	5	2
1466	3	7	7
1467	3	6	2
1468	2	9	6
1469	4	4	3

	YearsSinceLastPromotion	YearsWithCurrManager
0	0	5
1	1	7
2	0	0
3	3	0
4	2	2
...
1465	0	3
1466	1	7
1467	0	3
1468	0	8
1469	1	2

[1470 rows x 35 columns]>

To find Attrition Rate

```
data['Attrition'].value_counts(normalize=True)
```

Attrition

No 0.838776

Yes 0.161224

Name: proportion, dtype: float64

```
import matplotlib.pyplot as plt
```

```
import seaborn as sns
```

```
Attrition = data['Attrition'].value_counts(normalize=True)
```

```
ax = sns.barplot(x=Attrition.index, y=Attrition)
```

```
for p in ax.patches:
```

```
    ax.annotate(f'{p.get_height() * 100:.2f}%',  
                (p.get_x() + p.get_width() / 2., p.get_height()),  
                ha='center', va='center', fontsize=10, color='black', xytext=(0, 5),  
                textcoords='offset points')
```

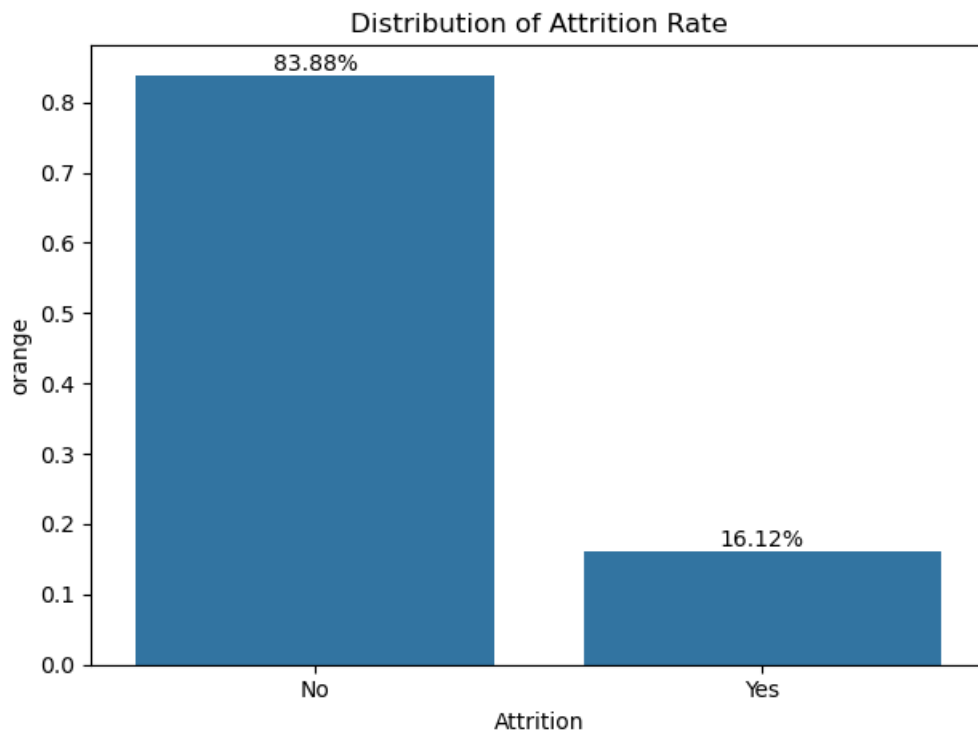
```
plt.title('Distribution of Attrition Rate')
```

```
plt.xlabel('Attrition')
```

```
plt.ylabel('Percentage')
```

```
plt.tight_layout()
```

```
plt.show()
```



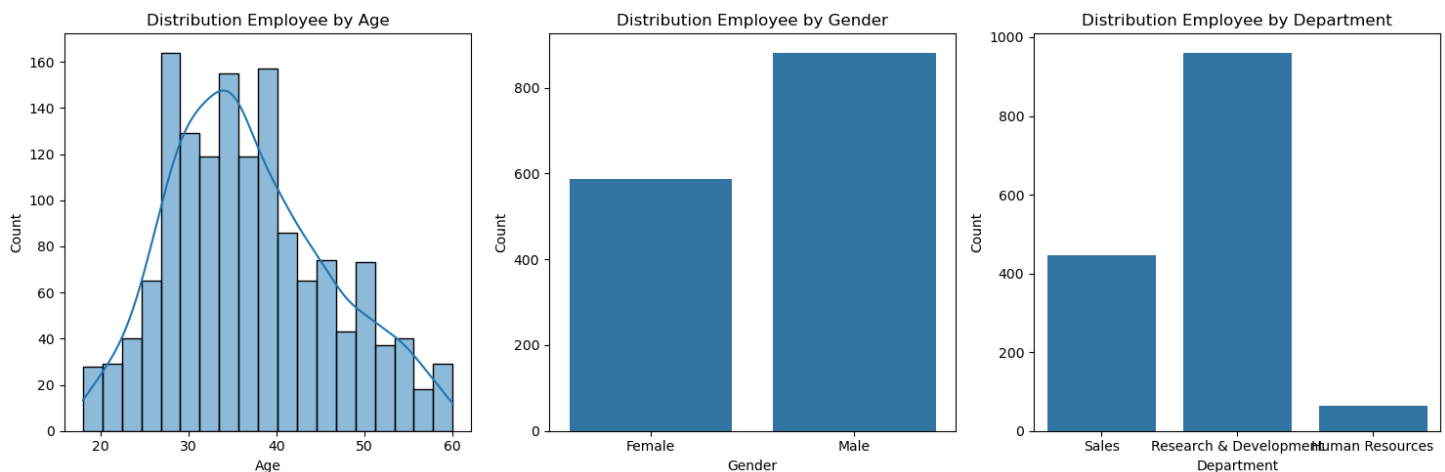
To Find Average tenure

```
avg_tenure = data['YearsAtCompany'].mean()
print(f'Average years of employee to leave the company years is')
print(avg_tenure)
```

Average years of employee to leave the company years is
7.0081632653061225

Plotting Distribution of Employee by Age, Employee by Gender and Employee by Department

```
fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(15,5))
sns.histplot(data=data, x='Age', kde=True, ax=axes[0])
axes[0].set_title('Distribution Employee by Age')
axes[0].set_xlabel('Age')
axes[0].set_ylabel('Count')
sns.countplot(data=data, x='Department', ax=axes[2])
axes[2].set_title('Distribution Employee by Department')
axes[2].set_xlabel('Department')
axes[2].set_ylabel('Count')
sns.countplot(data=data, x='Gender', ax=axes[1])
axes[1].set_title('Distribution Employee by Gender')
axes[1].set_xlabel('Gender')
axes[1].set_ylabel('Count')
plt.tight_layout()
```



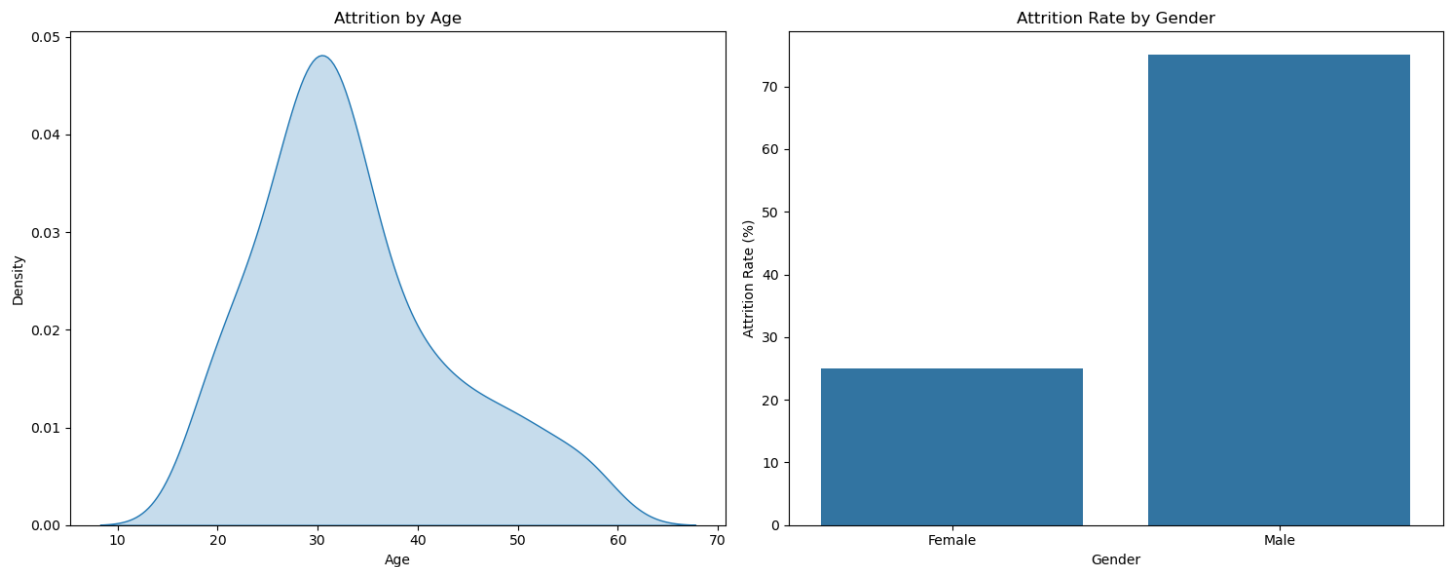
To Calculate Attrition by Age and Attrition Rate by Gender

```
def calculate_Attrition_rate(data, column):
    attrition_counts = data.groupby([column, 'Attrition']).size().unstack(fill_value=0)
    attrition_rate = attrition_counts['Yes'] / attrition_counts.sum(axis=1) * 100
    attrition_rate_data = attrition_rate.reset_index()
    attrition_rate_data.columns = [column, 'Attrition Rate']
```

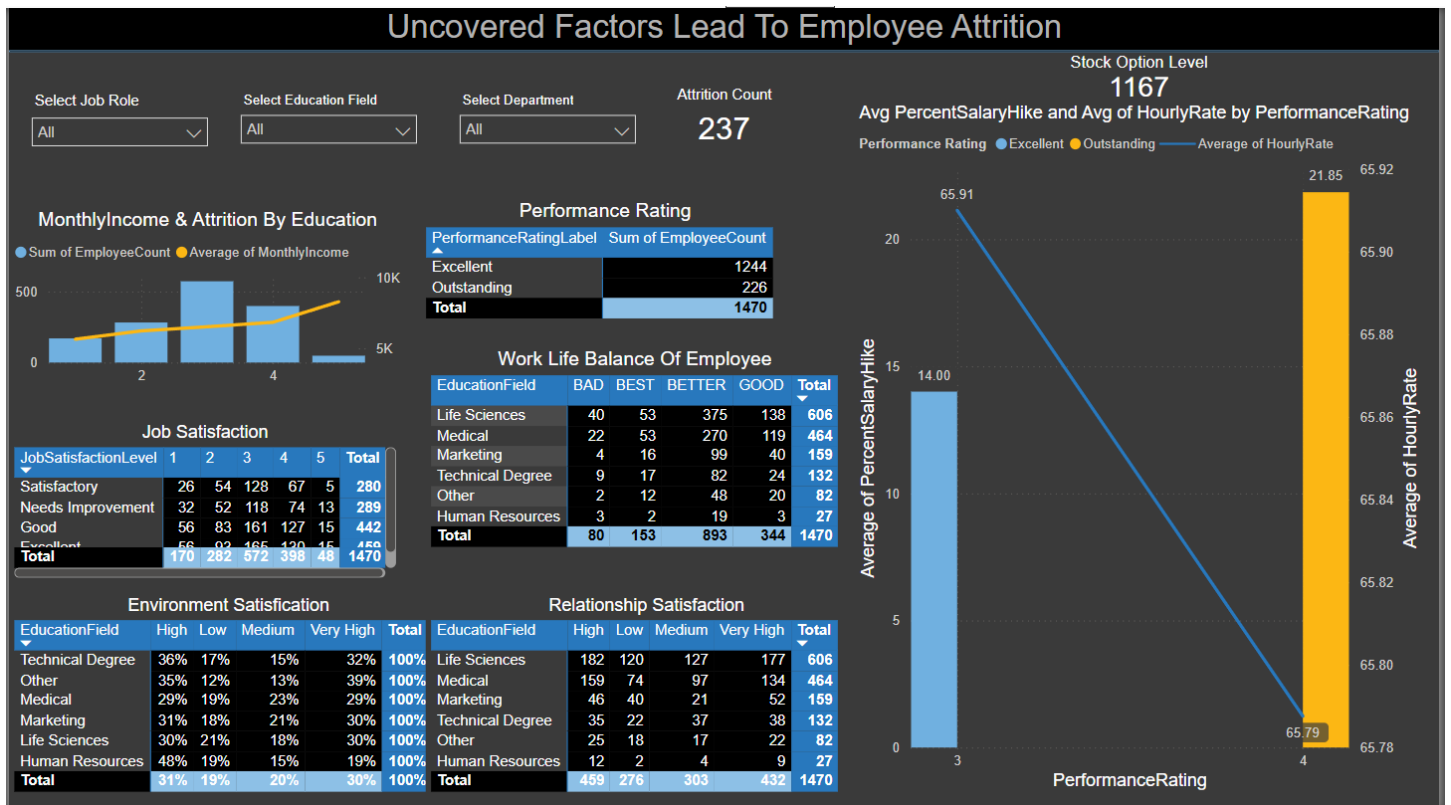
```

return attrition_rate_data
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(15,6))
# Plot 1: KDE plot of Age with Attrition hue
sns.kdeplot(data=data_attrition, x='Age', fill=True, ax=axes[0])
axes[0].set_title('Attrition by Age')
axes[0].set_xlabel('Age')
axes[0].set_ylabel('Density')
# Plot 2: Bar plot of Gender count with Attrition hue
attrition_rate_data = calculate_attrition_rate(data, 'Gender')
sns.barplot(data=attrition_rate_data, x='Gender', y='AttritionRate', ax=axes[1])
axes[1].set_title(f'Attrition Rate by Gender')
axes[1].set_xlabel('Gender')
axes[1].set_ylabel('Attrition Rate (%)')
plt.tight_layout()
plt.show()

```



Share :



- **ACT (Actions to Take)**

Based on the analysis of the HR attrition data, the following actions are recommended:

1. Employees in Sales and R&D, which show the highest attrition rates, should be offered flexible hours and remote work opportunities to reduce stress and improve work-life balance.
2. Since over 53% of employees who left were working overtime, it's crucial to track workloads and redistribute tasks to prevent employee burnout.
3. Job role satisfaction is a strong attrition driver. Run frequent anonymous employee engagement surveys to monitor satisfaction and act early on dissatisfaction.
4. Introduce bonuses and stock options for high performers, especially in roles like Sales Executive and Laboratory Technician which have higher attrition rates.
5. Establish clear and personalized career paths with defined promotion criteria. This will retain mid-career professionals who form a major chunk of attrition.

- **Suggestions**

1. Address Department-Specific Needs:
Tailor retention strategies for departments like Sales and R&D, where turnover is highest.
2. Target High-Risk Age Group:
Focus on employees aged 28–39 years with personalized development plans, as they form 50% of total attrition cases.
3. Support Low-Income Employees:
Many employees earning below \$3,200 per month are leaving. Consider salary adjustments or non-monetary benefits like learning stipends or flexible hours.
4. Improve Manager-Employee Relations:
Offer leadership training to managers to improve team engagement and communication.
5. Use Predictive Analytics:
Build and deploy a model using this dataset to predict attrition risk and act proactively with one-on-one interventions.

- **Conclusion :**

1. Attrition is strongly tied to employee workload, satisfaction, and compensation.
2. Employees in Sales, younger age groups, or those doing overtime are most at risk.
3. Implementing better work-life policies, performance-linked rewards, and Managerial engagement can improve retention.
4. ML models provide reliable prediction to support HR decision-making.

