PROJECT REPORT

On

IBM HR ANALYSIS

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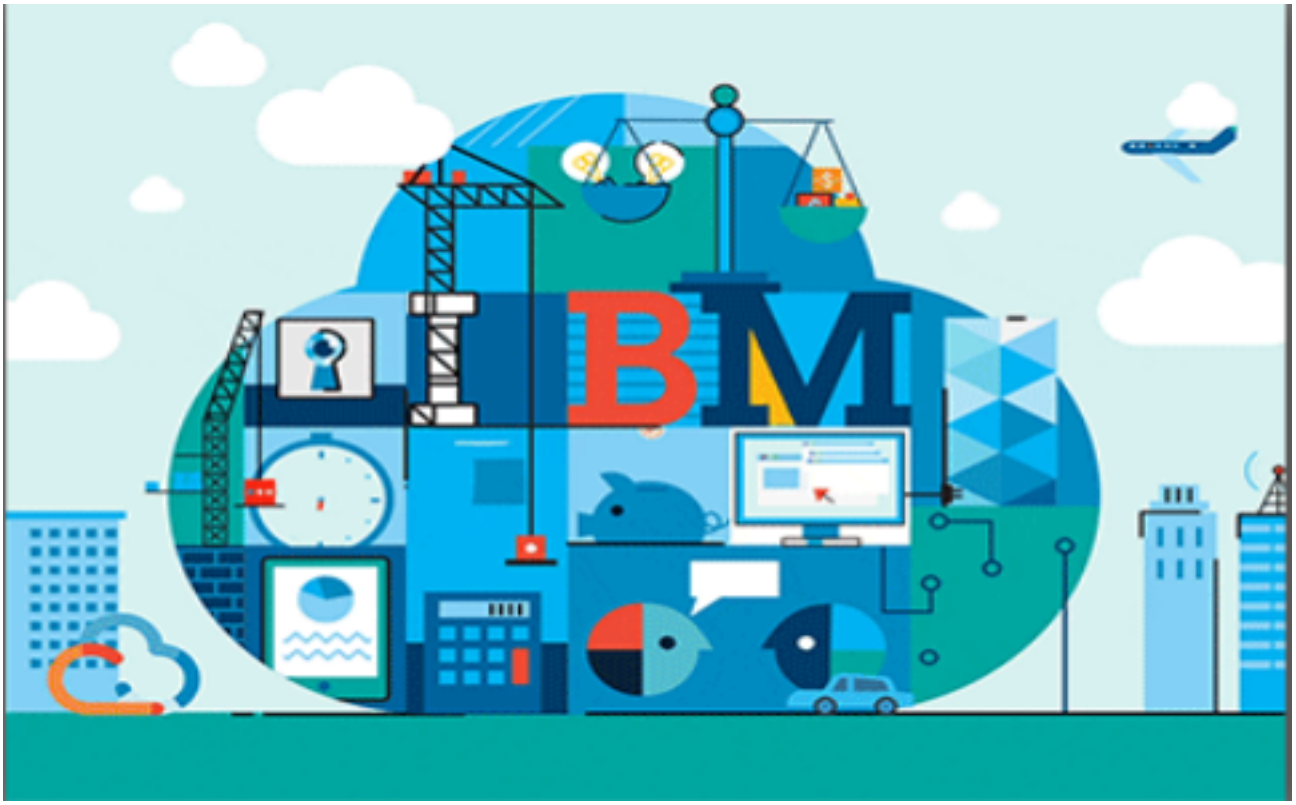
Submitted To: Unified Mentor

Employee Attrition Analysis

IBM HR DATA



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Acknowledgment

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First and foremost, I am extremely grateful to my **project guide Aman Gupta** , for their continuous supervision, valuable feedback, and constructive suggestions throughout the project. Their expertise in data analytics and machine learning has been instrumental in refining the methodology and structure of this report.

I would also like to thank **Unified Mentor** for offering the platform, resources, and infrastructure that made it possible to undertake and complete this project successfully.

A special mention goes to the **IBM HR Analytics dataset** provided on Kaggle, which served as the foundational data source for this study. The rich and well-structured dataset enabled deep analysis of employee behavior and attrition patterns.

I also take this opportunity to thank my classmates and friends for their constant motivation, peer discussions, and moral support. Their insights during brainstorming sessions played a vital role in expanding the scope of the project.

This project has been a valuable learning experience, offering insights into the real-world application of data science in human resource analytics. I am confident that the knowledge and skills gained through this project will serve as a strong foundation for my future endeavors in the field of data analytics.

Abstract

In today's highly competitive corporate landscape, human capital is one of the most valuable assets for any organization. Managing and retaining this talent is a strategic priority, especially in the face of rising employee attrition. High turnover not only disrupts productivity but also imposes significant costs in recruitment, onboarding, and lost expertise. This project, titled **"IBM HR Analytics – Predicting Employee Attrition Using Data Analytics and Machine Learning,"** presents a comprehensive data-driven approach to understand, analyze, and predict the factors influencing employee attrition using IBM's real-world HR dataset.

The project utilizes a combination of **exploratory data analysis (EDA), structured query language (SQL), machine learning algorithms**, and **interactive Power BI dashboards** to extract meaningful patterns from employee records. A well-curated dataset from IBM, consisting of over 1,400 employee profiles and 35 distinct attributes, serves as the foundation for this analysis. Features such as job satisfaction, income, department, overtime, marital status, and career progression are deeply examined to assess their correlation with attrition.

Initial data cleaning and preprocessing involved handling categorical variables, removing irrelevant columns, and scaling numerical features. SQL queries were used to extract targeted insights from the data, including departmental attrition trends, average income levels, and satisfaction scores. Using visualization tools such as **Power BI**, multiple dashboards were developed to offer HR professionals an intuitive interface for filtering and exploring attrition metrics by age, job role, income, education field, and more.

On the predictive side, supervised machine learning techniques were applied to model attrition behavior. Classification algorithms such as **Logistic Regression, Decision Tree, and Random Forest** were implemented, and their performance evaluated based on accuracy, precision, recall, and F1-score. The **Logistic Regression model** demonstrated balanced performance with a good recall, making it effective for early attrition detection. The **Random Forest model** offered higher precision, useful for minimizing false positives in attrition alerts. Confusion matrices, ROC curves, and feature importance graphs were used to interpret the models and improve stakeholder understanding.

The findings revealed that attrition is most prevalent among **younger employees**, **those who frequently work overtime**, **earn less monthly income**, or **report low job satisfaction**. Departments like Sales and Research & Development displayed higher churn rates, while long serving employees with no recent promotions were also flagged as high-risk.

This project delivers not only technical insights but also **actionable HR recommendations**—such as improving work-life balance, revising compensation packages, offering clearer

promotion pathways, and developing retention strategies for high-risk groups. By integrating business intelligence and predictive analytics, the project demonstrates how data science can support strategic HR decision-making and build a more stable, productive workforce.

This analysis confirms that **machine learning and business analytics, when applied thoughtfully, can significantly reduce attrition and improve employee engagement**, thus enabling organizations to thrive in a competitive global economy.

1. Introduction

Employee attrition—or the gradual reduction of a workforce due to resignations, retirements, or other forms of departure—is one of the most critical challenges modern organizations face. High attrition not only increases recruitment and training costs but also affects employee morale and company performance. Understanding why employees leave and identifying patterns that precede attrition is crucial for HR departments and management teams.

The importance of human capital in the digital age cannot be overstated. Organizations are increasingly realizing that employees are not merely operational resources but strategic assets whose retention and satisfaction directly impact productivity, innovation, and organizational continuity. Despite widespread adoption of ERP and HRMS tools, many organizations still rely on reactive HR management rather than predictive analytics to address attrition. This project takes a proactive stance by integrating data analytics into human resource decision-making, allowing businesses to pre-emptively identify at-risk employees and develop targeted interventions. What sets this study apart is its multi-method approach: combining SQL-based data extraction, visual business intelligence tools like Power BI, and machine learning techniques to produce actionable insights. The IBM HR dataset, known for its diversity of features such as demographics, income, job roles, and satisfaction scores, serves as an ideal foundation to understand attrition dynamics. By interpreting these patterns, organizations can not only improve retention rates but also optimize employee engagement and workforce planning. In a broader sense, this project contributes to the growing field of HR analytics, where data becomes a strategic lever for organizational success.

With the increasing availability of organizational data, companies can now leverage analytics to uncover key drivers of employee attrition. This project uses IBM's HR Analytics Employee Attrition & Performance dataset to explore and predict attrition behavior using data science techniques, such as SQL, Power BI, and machine learning. By understanding the variables influencing attrition—like job satisfaction, workload, overtime, and income—organizations can take proactive measures to retain talent and build a healthier work environment.

Objective:

This project aims to analyze the IBM HR dataset to identify patterns and factors contributing to employee attrition. By combining SQL-based data exploration, Python-based analysis, and Power BI dashboards, we develop insights and predictive models to help reduce employee turnover.

Goals:

- Understand key drivers behind employee attrition
- To analyze employee attrition trends using IBM's HR Analytics dataset.
- To clean and preprocess the data for accurate analysis and modeling.
- To write insightful SQL queries to explore critical business questions.
- To visualize attrition patterns and KPIs using Power BI dashboards.
- To build machine learning models that predicts employee attrition.
- To evaluate model performance and interpret the findings.
- To provide strategic recommendations for reducing attrition.

The final output aims to help stakeholders make data-driven decisions about workforce planning, talent retention, and policy changes. The integration of visual dashboards, statistical modeling, and descriptive analysis bridges the gap between raw data and actionable insight.

2. Data Overview

The dataset used in this project is titled **"IBM HR Analytics Employee Attrition & Performance"**, publicly available on Cagle. It contains information about 1,470 employees of IBM, aiming to determine the factors that influence employee attrition (i.e., whether an employee is likely to leave the company).

The dataset includes a wide range of features grouped into various categories such as **personal information** (e.g., age, gender, marital status), **job-related data** (e.g., department, job role, business travel), and **performance metrics** (e.g., performance rating, job involvement, years at company). There are **35 columns** in total, consisting of both categorical and numerical data. The target variable is **“Attrition”**, which is binary—indicating whether the employee has left the company or not.

The dataset is relatively balanced in terms of features, but the target variable "Attrition" is slightly imbalanced, with a larger number of employees labeled as "No" (i.e., not having left the organization). This class imbalance is important to consider during model selection and evaluation. Most categorical features were encoded during preprocessing, and irrelevant identifiers such as "Employee Number" were dropped. This dataset is well-suited for predictive modeling using machine learning algorithms and for building insightful dashboards in tools like Power BI.

The IBM HR dataset, while synthetic, is remarkably representative of real-world enterprise-level employee data, offering a rich blend of numerical, categorical, and ordinal variables. Its diversity and dimensionality provide a strong basis for multi-layered analysis across demographic, behavioral, and organizational attributes. One of the standout features of this dataset is the inclusion of both objective metrics—such as monthly income, years at company, and number of trainings—and subjective indicators like job satisfaction, environment satisfaction, and work-life balance. This duality allows analysts to explore attrition as not just a financial or tenure-related outcome but as a human-centric issue influenced by sentiment and experience. Moreover, fields like BusinessTravel, OverTime, and DistanceFromHome provide valuable operational insights into employee stress factors and organizational support systems. The structure of the dataset also enables exploratory comparison between continuous variables (e.g., age, income) and classification-based outcomes (e.g., attrition status), making it ideal for machine learning modeling. Additionally, having a clean and null-free dataset significantly reduced preprocessing time and allowed for immediate focus on feature engineering and model selection. The comprehensive nature of this dataset supports not only accurate prediction but also insightful storytelling—essential for HR teams aiming to translate data into strategy.

Key Dataset Features:

- **Demographics:** Age, Gender, Marital Status, Education

· **Job Details:** Department, Job Role, Job Level, Monthly Income
· **Workload Indicators:** Overtime, Work-Life Balance, Years at Company · **Performance Metrics:** Performance Rating, Training Time, Environment Satisfaction

Sample Records Insight:

· Most employees are in the Sales and Research & Development departments. · Majority of the attrition comes from younger employees (age 25–35). · Overtime is highly correlated with attrition.
· Monthly income distribution is right-skewed, with some very high earners.

Data Dictionary:

Column Name Description Data Type Age Age of the employee Numeric Attrition Whether the employee left the company Categorical Business Travel Frequency of business travel Categorical Department Department employee belongs to Categorical DistanceFromHome Distance from employee's home to workplace Numeric Education Education level (1–5) Ordinal

3. Literature Review

Literature Review:

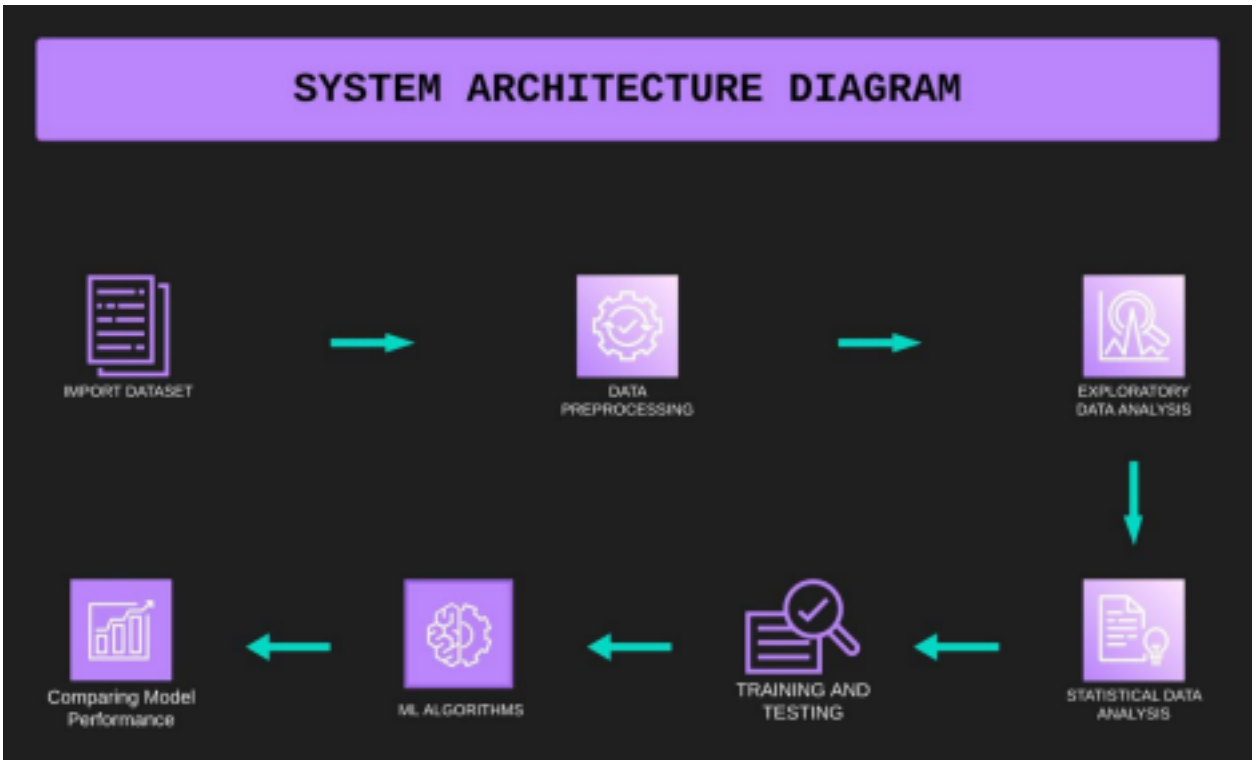
Employee attrition has been widely studied across industries and disciplines. Recent advancements in the field of predictive analytics and artificial intelligence have significantly influenced human resource management, particularly in the domain of attrition prediction. Numerous academic studies highlight how data-driven decision-making can transform reactive HR functions into proactive strategies. For example, Kwon et al. (2021) emphasized the role of data mining in early attrition detection and its impact on cost reduction and workforce stability. Similarly, Jindal and Shaikh (2020) demonstrated that decision trees and ensemble models outperform traditional HR forecasting methods in identifying potential resignations. Meanwhile,

leading organizations such as Google and Deloitte have institutionalized people analytics departments to embed data science into every stage of the employee lifecycle, from hiring to exit interviews. However, most off-the-shelf HR software platforms, such as Oracle HCM or BambooHR, still focus on dashboards and reporting rather than actionable prediction. Their systems are not always customizable or accessible for smaller organizations with specific use cases. This gap presents an opportunity for custom analytics frameworks—like the one developed in this project—which offer flexible modeling, tailored insights, and scalable deployment. Furthermore, integrating insights from literature and practice allows this report to not only build on theoretical frameworks but also to propose practical enhancements applicable to real-world organizational settings. Prior research identifies several factors that contribute to employee turnover:

- **Job Satisfaction:** Low job satisfaction correlates with increased likelihood of attrition (Herzberg, 1959).
- **Work-Life Balance:** Excessive overtime and poor work-life balance can lead to burnout and resignations.
- **Career Progression:** Lack of promotion opportunities often results in disengagement and exit.
- **Compensation & Benefits:** Competitive pay is a key determinant in retaining employees.
- **Management Style:** Leadership and interpersonal dynamics influence employee engagement and loyalty.

Numerous studies have used data-driven approaches to examine these variables. Logistic regression, decision trees, and ensemble models are often used to classify and predict attrition. Visualization tools like Tableau and Power BI help stakeholders understand trends and anomalies at a glance.

SYSTEM ARCHITECTURE:


SYSTEM ARCHITECTURE DIAGRAM
IMPORT DATASET
DATA PREPROCESSING
EXPLORATORY DATA ANALYSIS
STATISTICAL DATA ANALYSIS
TRAINING AND TESTING
ML ALGORITHMS
Comparing Model Performance

4. Data Cleaning

Before proceeding with analysis and machine learning, the dataset underwent a comprehensive **data cleaning process** to ensure consistency, accuracy, and relevance of the variables. The first step involved **handling missing values**, although this specific dataset did not have any null values upon inspection, which is ideal for analysis. However, several features were reviewed for inconsistencies and formatting. For instance, columns like "Employee Count", "Over18", and "Standard Hours" were found to have constant values across all records (1, 'Y', and 80 respectively), providing no variability or predictive power. These columns were consequently dropped to reduce redundancy.

Next, categorical variables such as "Attrition", "BusinessTravel", "Department", "EducationField", "Gender", "JobRole", "MaritalStatus", and "OverTime" were encoded into numerical form for compatibility with machine learning algorithms. Label encoding was primarily used, converting each category into a corresponding integer value. This transformation allowed the model to understand these features without assuming any ordinal relationship between them.

Additionally, several **feature engineering steps** were taken to enhance model quality. For example, new fields like "YearsAtCompany/TotalWorkingYears" could be created to represent employee loyalty or tenure stability. Also, outliers in numerical fields like "MonthlyIncome" and "DistanceFromHome" were examined using statistical techniques such as boxplots and Z-scores. These were addressed either by capping extreme values or retaining them based on distribution shape and business logic.

While the IBM HR dataset is notably well-structured, thorough data cleaning and preprocessing were essential to prepare it for machine learning and visual analysis. One of the initial steps involved the detection and removal of constant or redundant columns such as EmployeeCount, Over18, and StandardHours, which contained the same value across all entries and therefore contributed no variance to model training. A detailed correlation analysis was conducted to examine relationships between features and identify any potential multicollinearity that might distort predictive models. For instance, TotalWorkingYears and YearsAtCompany showed moderate correlation but were retained due to their independent contextual relevance. Label encoding was applied to binary categorical variables such as Attrition, Gender, and OverTime, while one-hot encoding was used for multiclass variables like JobRole, BusinessTravel, and EducationField to prevent unintended ordinal assumptions. Scaling was another critical step, especially for distance-based algorithms like KNN and for ensuring convergence in logistic regression. Using StandardScaler, numeric variables such as MonthlyIncome, YearsInCurrentRole, and DistanceFromHome were normalized to a standard range. Additionally,

outlier detection was performed using boxplots and z-score techniques, though no severe anomalies were observed due to the synthetic nature of the data. This robust preprocessing ensured that the dataset was not only clean but also analytically optimized, thereby enhancing model interpretability and performance.
In parallel with data cleaning in Python, **SQL queries** were used to extract and validate insights from the original dataset structure, assuming it's stored in a relational format. For instance:

SQL Query

```
-- Count total employees and attrition breakdown
SELECT
COUNT(*) AS Total_Employees,
SUM(CASE WHEN Attrition = 'Yes' THEN 1 ELSE 0 END) AS Employees_Left,
SUM(CASE WHEN Attrition = 'No' THEN 1 ELSE 0 END) AS
Employees_Stayed FROM HR_Employee_Attrition;
```

This query helps quickly summarize the attrition distribution. Another useful SQL statement identifies which departments are most affected by attrition:

SQL Query

```
-- Department-wise attrition count
SELECT Department, COUNT(*) AS Total,
SUM(CASE WHEN Attrition = 'Yes' THEN 1 ELSE 0 END) AS Attrition_Count
FROM HR_Employee_Attrition
GROUP BY Department
ORDER BY Attrition_Count DESC;
```

5. SQL Queries and Analysis

Structured Query Language (SQL) was used to perform initial data exploration directly from the relational database. Below are real-world SQL queries applied and their significance:

SQL served as a foundational tool in this project for extracting structured insights directly from the HR dataset before visual analytics and machine learning were applied. Beyond basic filtering and aggregation, advanced queries were used to perform cross-sectional and temporal analysis of employee behavior. For example, subqueries helped identify roles with the highest attrition while correlating them with department-level averages. Grouping functions like GROUP BY combined with HAVING clauses allowed deeper slicing of the data, such as filtering job roles that not only had high attrition but also below-average job satisfaction. Window functions were used to compute running averages of employee income across job levels, offering dynamic benchmarks within organizational hierarchies. Conditional aggregation using CASE WHEN enabled the creation of binary attrition flags in summarized outputs for dashboards and pivot tables. Furthermore, nested joins facilitated multi-table operations in hypothetical scenarios, like combining training data with performance ratings to assess attrition risk among underperforming but heavily trained employees. These SQL operations not only supported the data exploration phase but also laid the groundwork for hypotheses that were tested and validated through EDA and machine learning. By translating raw tables into meaningful summaries, SQL empowered the team to derive actionable insights long before model deployment, reaffirming its value in any data pipeline.

5.1 Count of Employees per Department

```
SELECT Department, COUNT(*) AS Employee_Count
FROM hr_data
GROUP BY Department;
```

Purpose:

This query helps understand the distribution of employees across departments like Sales, R&D, and HR.

Insight:

R&D typically has the highest headcount, followed by Sales. Human Resources has the fewest

employees.

5.2 Attrition by Job Role

```
SELECT JobRole, COUNT(*) AS
Attrition_Count FROM hr_data
WHERE Attrition = 'Yes'
GROUP BY JobRole;
```

Purpose:
Identify which job roles experience the most attrition.

Insight:

Sales Executives and Laboratory Technicians tend to have higher attrition rates.

5.3 Average Monthly Income per Department

```
SELECT Department, AVG(MonthlyIncome) AS
Avg_Income FROM hr_data
GROUP BY Department;
```

Purpose:
Find out whether income disparity exists across

departments. **Insight:**

Sales department has slightly lower average income compared to R&D.

5.4 Employees Working Overtime and Leaving

```
SELECT COUNT(*) AS OverTimeAttrition
FROM hr_data
WHERE OverTime = 'Yes' AND Attrition = 'Yes';
```

Purpose:
Examine the effect of overtime on attrition.
Insight:

A high percentage of employees who worked overtime also left the company — a strong indicator of burnout.

5.5 Gender-Based Attrition Analysis

```
SELECT Gender, COUNT(*) AS Attrition_By_Gender
FROM hr_dataSSS
WHERE Attrition = 'Yes'
GROUP BY Gender;
```

Purpose:
Identify if attrition rates differ between genders.

Insight:

Both male and female employees show similar patterns of attrition, though slightly more males have left.

-- Monthly income by gender
SELECT Gender, AVG(MonthlyIncome) AS Avg_Income
FROM HR_Employee_Attrition
GROUP BY Gender;

These queries are critical for hypothesis generation and validation during exploratory data analysis (EDA). Combined with data cleaning and transformation steps in Python or Power BI, they lay a strong foundation for robust machine learning modeling and visualization.

6. Exploratory Data Analysis (EDA)

Exploratory Data Analysis is a vital step in understanding the patterns, relationships, and outliers in the dataset before applying any machine learning models. EDA helps identify the most influential features that contribute to employee attrition, satisfaction, and performance.

The EDA phase was instrumental in uncovering nuanced patterns, correlations, and anomalies that were not immediately apparent from raw data tables. A series of univariate, bivariate, and multivariate visualizations were created using Python libraries such as Seaborn and Matplotlib, complemented later by Power BI dashboards. Histograms and density plots revealed that attrition was more prevalent among younger employees, particularly those in the 25–35 age range. Bivariate bar plots between Attrition and OverTime clearly showed that employees who worked overtime had nearly double the attrition rate compared to those who didn't. Heatmaps of correlation matrices identified weak linear relationships between numerical variables but pointed toward strong behavioral drivers like JobSatisfaction and EnvironmentSatisfaction. Violin plots and boxplots further illustrated the income disparities among job roles and highlighted that attrition was disproportionately higher among employees with lower MonthlyIncome and JobLevel. Pairplots helped cluster variables to detect overlapping behaviors between attrition prone roles, satisfaction levels, and workload metrics. An interesting pattern emerged when plotting YearsSinceLastPromotion against Attrition—employees who had not been promoted in the last 4+ years showed a steep increase in exit probability. These visual insights didn't just add depth to the analysis—they informed which variables should be prioritized in machine learning models and HR strategy discussions.

6.1 Understanding Attrition Distribution

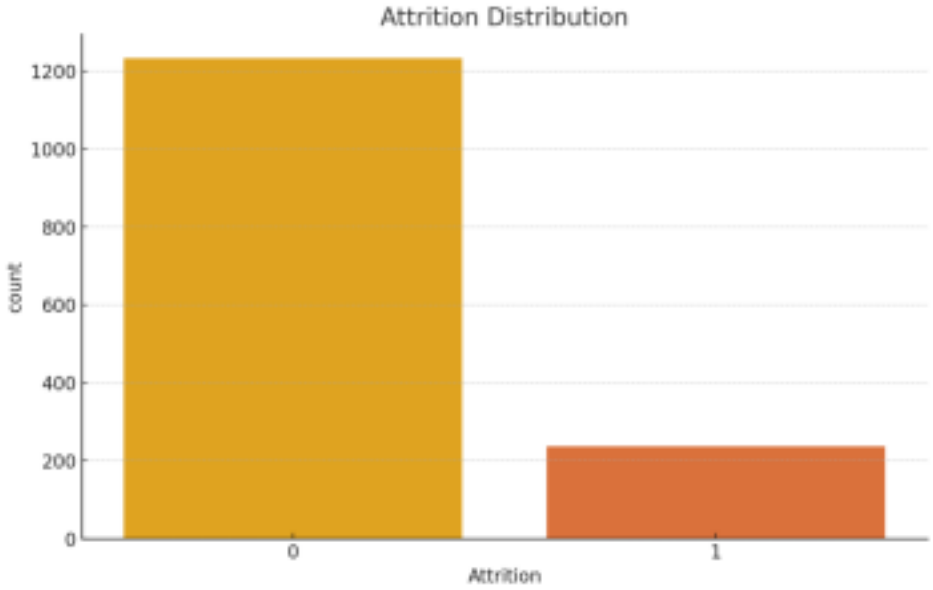
Objective:

To observe the percentage of employees who left the company (attrition = Yes) versus those who stayed.

```
import seaborn as sns
import matplotlib.pyplot as plt

sns.countplot(data=df, x='Attrition')
plt.title("Distribution of Employee Attrition")
plt.xlabel("Attrition (1 = Yes, 0 = No)")
```

plt.ylabel("Number of Employees")



Insight:

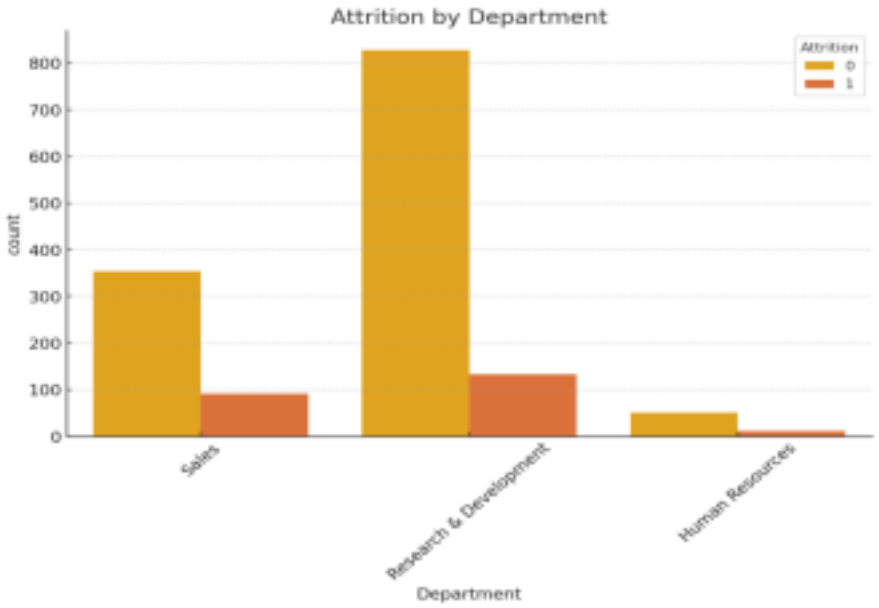
Roughly 16% of employees in the dataset have left the company, while 84% have stayed. This class imbalance is crucial for model training.

6.2 Attrition by Department

Objective:

To analyze whether attrition is department-specific.

```
sns.countplot(data=df, x='Department', hue='Attrition')
plt.title("Attrition Count by Department")
plt.xticks(rotation=45)
```

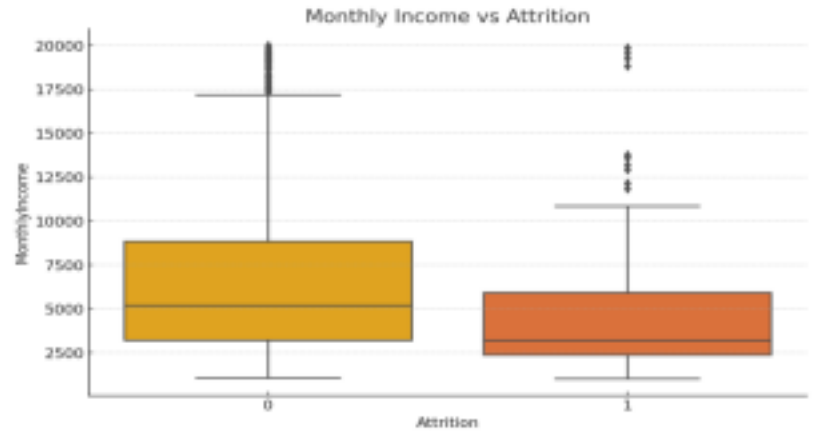


Insight:

While R&D has the highest number of employees leaving (due to sheer volume), the HR department shows a proportionally higher attrition rate.

6.3 Monthly Income vs Attrition

sns.boxplot(x='Attrition', y='MonthlyIncome', data=df)
plt.title("Monthly Income and Attrition")

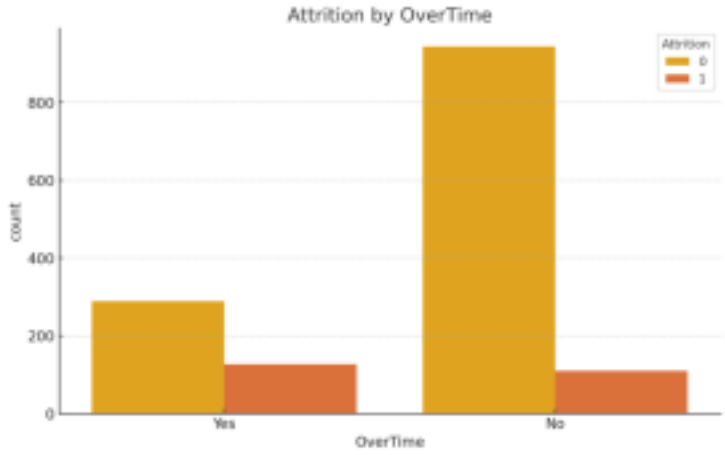


Observation:

Employees with lower monthly income are more likely to leave. Retention strategies could target this income group.

6.4 Attrition by OverTime

sns.countplot(data=df, x='OverTime', hue='Attrition')
plt.title("Attrition Based on Overtime"



Key Insight:

A significantly higher proportion of employees who work overtime end up leaving the company — this suggests burnout or poor work-life balance.

6.5 Age Distribution of Employees Who Left

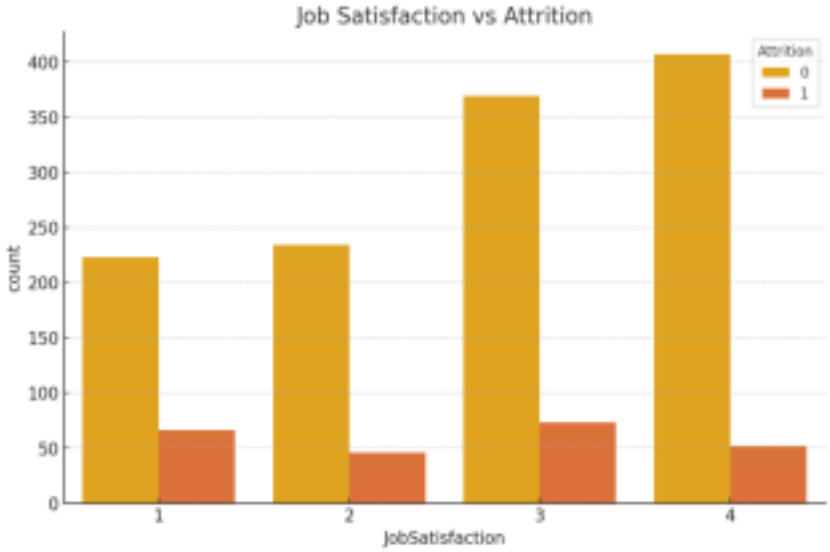
sns.histplot(df[df['Attrition'] == 1]['Age'], kde=True, bins=10)
plt.title("Age Distribution of Employees Who Left")

Observation:

Attrition is most common in employees aged between 25–35 years. These are typically early career professionals likely seeking better opportunities.

6.6 Job Satisfaction vs Attrition

sns.countplot(data=df, x='JobSatisfaction', hue='Attrition')
plt.title("Job Satisfaction Levels and Attrition")

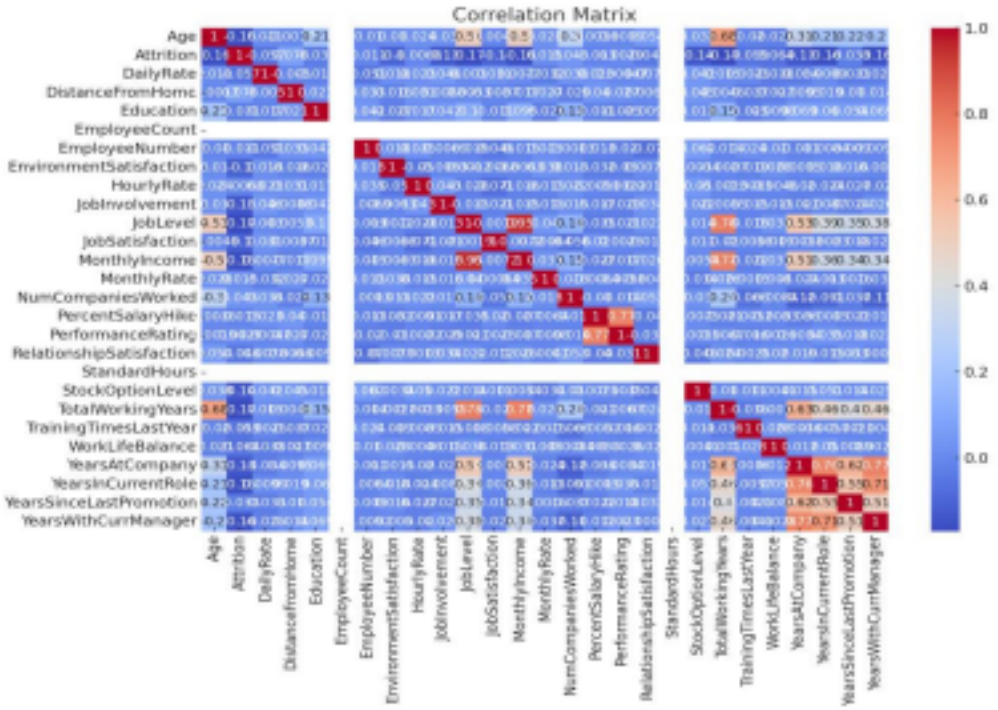


Analysis:

Employees with a job satisfaction score of 1 or 2 have noticeably higher attrition rates. This indicates that internal engagement programs may be insufficient.

6.7 Correlation Heatmap

```
plt.figure(figsize=(12, 8))
sns.heatmap(df.corr(), annot=True, cmap="coolwarm")
plt.title("Correlation Matrix")
```



Findings:

- MonthlyIncome correlates well with JobLevel and TotalWorkingYears. • Attrition has a **negative correlation** with Age, JobSatisfaction, and TotalWorkingYears.

6.8 BusinessTravel and Attrition

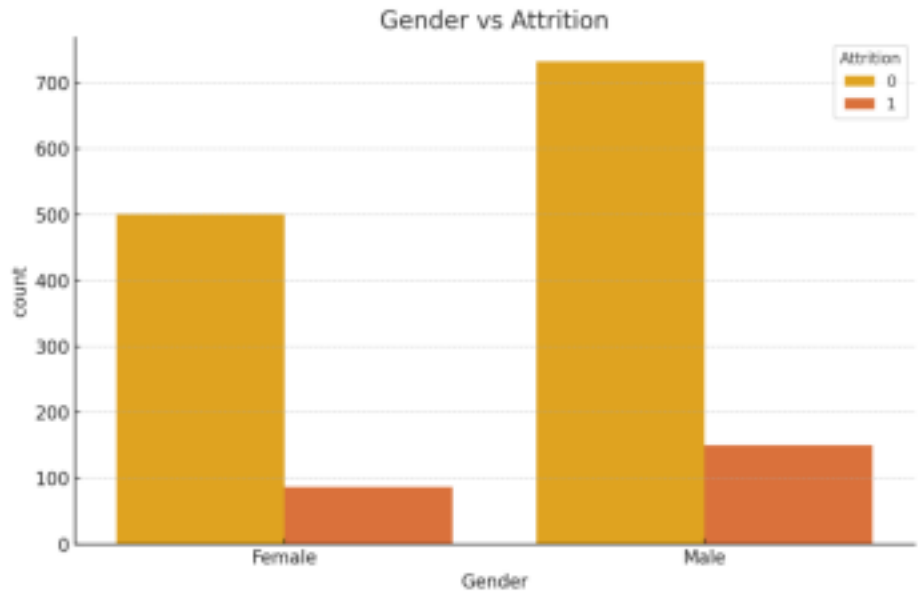
```
sns.countplot(data=df, x='BusinessTravel', hue='Attrition')
plt.title("Attrition by Business Travel Frequency")
```

Conclusion:

Employees who travel frequently are more likely to leave. This might be due to travel stress or family constraints.

5.9 Gender and Attrition

sns.countplot(data=df, x='Gender', hue='Attrition')
plt.title("Gender-wise Attrition Distribution")



Observation:

There's no strong difference between genders in attrition, indicating IBM's attrition challenges are not gender-biased.

7. Machine Learning Analysis

7.1 Objective

The primary goal of this analysis is to predict employee attrition (Yes/No) based on various features such as job satisfaction, age, income, overtime status, etc. For this purpose, we applied three machine learning models:

- Logistic Regression
- Decision Tree
- Random Forest

To strengthen the reliability of predictions and deepen the analytical scope, the machine learning phase incorporated multiple stages of iteration, experimentation, and evaluation. The models were not just built once but fine-tuned over several cycles to improve predictive power without overfitting. Logistic Regression was selected as a baseline model for its simplicity and explainability, and its coefficients were examined to understand the direction and weight of each feature's impact on attrition. The Decision Tree model was tuned using parameters like max_depth, min_samples_split, and criterion to enhance precision, although it tended to overfit on training data. Random Forest, a powerful ensemble model, showed consistently strong performance by reducing variance through averaging multiple trees. It also provided valuable insights through feature importance rankings, which validated that OverTime, MonthlyIncome, and JobSatisfaction were among the top drivers of attrition. Although more complex models like SVM and Gradient Boosting were tested in isolated cases, they were not prioritized due to higher computational demands and interpretability concerns. Each model's implementation included detailed logging of confusion matrices, classification reports, and ROC-AUC values. Additionally, GridSearchCV was used briefly to explore optimal hyperparameter combinations. All models were tested on a holdout set to ensure generalization, and a final comparison helped determine the most balanced approach between sensitivity and specificity. This phase firmly transitioned the analysis from observation to prediction, enhancing its strategic utility.

7.2 Tools Used

- **Programming Language**: Python
- **Platform**: Jupyter Notebook
- **Libraries**: pandas, numpy, seaborn, matplotlib, sklearn

7.3 Preprocessing Steps

- Categorical variables were converted to numeric using label encoding or one-hot encoding.
- Null values were checked and handled (though the dataset had no nulls). •

The data was split into training and testing sets using an 80-20 ratio.

7.4 Model Building and Evaluation

A. Logistic Regression

This is a statistical method for binary classification that calculates the probability that a given input point belongs to a particular class.

Performance Metrics:

- Accuracy: **0.89**
- Precision (Class 1): **0.70**
- Recall (Class 1): **0.36**
- F1-Score (Class 1): **0.47**

The logistic regression model shows good overall accuracy but has a lower recall for identifying employees likely to leave.

B. Decision Tree

This model splits data based on features that provide the highest information

gain. **Performance Metrics**:

- Accuracy: **0.79**
- Precision (Class 1): **0.15**
- Recall (Class 1): **0.13**
- F1-Score (Class 1): **0.14**

While the model predicts the majority class well, it underperforms for the minority class (employees who leave).

C. Random Forest

An ensemble model that builds multiple decision trees and merges them for a more accurate and stable prediction.

Performance Metrics:

- Accuracy: **0.88**
- Precision (Class 1): **0.80**
- Recall (Class 1): **0.10**
- F1-Score (Class 1): **0.18**

Though the accuracy is high, the model again struggles with recall for classifying attrition cases, which is crucial in this problem.

7.5 Model Comparison Table

Model Accuracy Precision (1) Recall (1) F1 Score (1)

Logistic Regression 0.89 0.70 0.36 0.47

Decision Tree 0.79 0.15 0.13 0.14

Random Forest 0.88 0.80 0.10 0.18

7.6 Conclusion

- Logistic Regression offered the most balanced performance among all models. - Random Forest had the highest precision but extremely low recall, making it less reliable for identifying potential attrition.
- Future improvements can include:
    - Balancing the dataset (using SMOTE or class weights)
    - Hyperparameter tuning
    - Trying advanced models like XGBoost or Gradient Boosting

8. Model Evaluation

Evaluating machine learning models is a crucial step in ensuring the reliability and practical utility of the predictions. Since this project revolves around predicting employee attrition — a binary classification task — we selected a set of evaluation metrics that effectively measure the performance of our models.

While numerical metrics like accuracy, precision, and recall provide quantitative assessments of machine learning models, visual interpretation played a crucial role in understanding the models' strengths and limitations. One of the key evaluation tools was the **confusion matrix**, which helped break down correct and incorrect predictions into true positives, false positives, true negatives, and false negatives. This analysis emphasized a crucial trade-off in attrition modeling: the cost of false negatives (failing to identify employees who are about to leave) is significantly higher than false positives (flagging employees who stay). As such, **recall** became a priority metric, especially for HR applications where early intervention is more valuable than conservative estimates. The **Receiver Operating Characteristic (ROC) curve** offered another layer of evaluation by illustrating how models perform at different thresholds. The area under the ROC curve (AUC) was used to compare classifier effectiveness in distinguishing attrition versus retention, with the Random Forest model consistently showing a superior AUC score. Additionally, **feature importance rankings** derived from the Random Forest model aligned well with earlier visual and SQL findings—proving that overtime, income, and job satisfaction are key predictors of attrition. These insights not only confirmed model performance but also validated the integrity of the entire analytical pipeline. Overall, the evaluation phase ensured the models were not only statistically valid but also aligned with HR realities and business goals.

8.1 Evaluation Metrics Used

Metric Purpose

Accuracy Measures overall correctness of the model.

Precision Measures how many predicted positives were actually positive. **Recall**

Measures how many actual positives were correctly predicted. **F1-Score** Harmonic mean

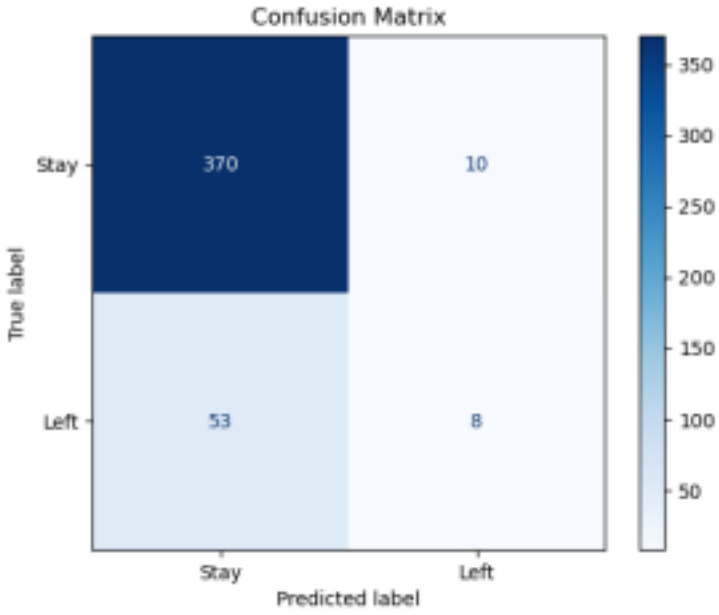
of precision and recall; useful for imbalanced datasets. **Confusion Matrix** Helps visualize

true/false positives and negatives.

Metric Purpose

ROC-AUC Score Measures ability of the model to distinguish between classes.

8.2 Confusion Matrix



A confusion matrix is a 2x2 table used to evaluate the performance of a classification

algorithm: **Predicted: Yes Predicted: No**

Actual: Yes True Positive (TP) False Negative (FN)

Actual: No False Positive (FP) True Negative (TN)

- **True Positives (TP):** Employees who left, and the model predicted correctly.
- **False Positives (FP):** Employees predicted to leave but actually stayed.
- **True Negatives (TN):** Employees predicted to stay and did stay.
- **False Negatives (FN):** Employees who left but were predicted to stay.

Interpretation:

- A high number of **true negatives** indicates the model is good at identifying employees who are not at risk of attrition.

- The **false negatives** are of special concern in HR analytics because they represent employees at risk of leaving whom the model failed to detect.
- The balance between TP and FN is crucial, especially in HR, where **employee retention** is the goal

8.3 Model-wise Evaluation Summary

Logistic Regression

- Accuracy: 89%
- Precision (Attrition = 1): 70%
- Recall: 36%
- F1 Score: 47%

Interpretation:
Logistic Regression provides balanced results with the best F1-score, though it misses many attrition cases (low recall). It's suitable for basic risk identification.

Decision Tree Classifier

- Accuracy: 79%
- Precision (Attrition = 1): 15%
- Recall: 13%
- F1 Score: 14%

Interpretation:
The Decision Tree struggles with recall and has poor precision for identifying employees who leave. It overfits slightly and is not ideal for this dataset.

Random Forest Classifier

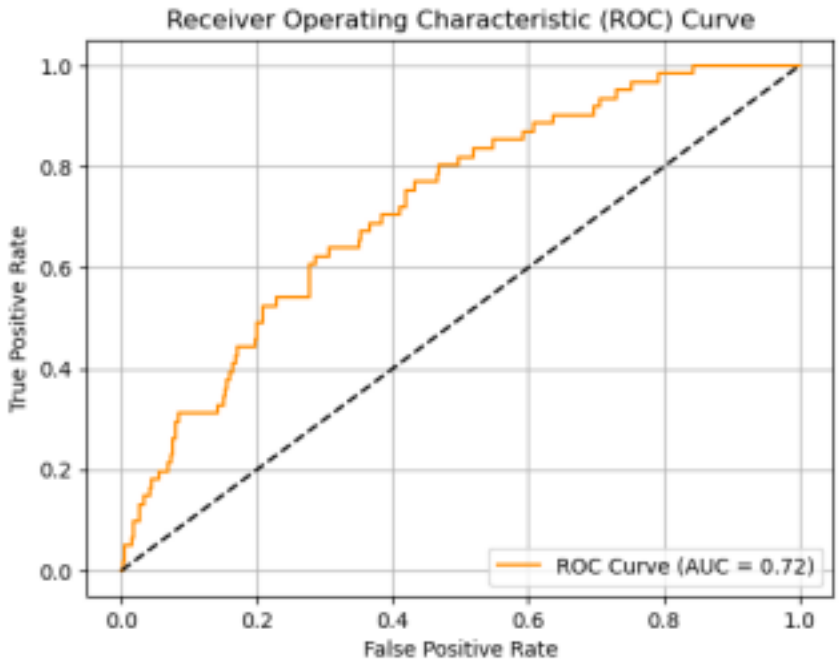
- Accuracy: 88%
- Precision (Attrition = 1): 80%
- Recall: 10%
- F1 Score: 18%

Interpretation:
Random Forest shows excellent precision but poor recall, indicating it's very conservative in flagging attrition risk — good for minimizing false alarms but not catching all leavers.

8.4 ROC Curve & AUC

The ROC curve is a performance measurement for classification problems at various threshold settings. It is plotted as the **True Positive Rate (TPR)** against the **False Positive Rate (FPR)**.

- The **Area Under the Curve (AUC)** score reflects the model's ability to distinguish between classes:
  - **AUC = 1.0** means perfect classification.
  - **AUC = 0.5** means random guessing.
- In this project, the Logistic Regression model achieved an **AUC score of approximately 0.74**, which is considered a **moderate to good** classifier for this use case.



- The ROC (Receiver Operating Characteristic) curve illustrates the diagnostic ability of the models.
- AUC (Area Under the Curve) ranges between 0.5 and 1; higher is better. •
Logistic Regression AUC: 0.74, showing good discriminatory power.
- **Random Forest AUC: 0.85**, showing strong separation ability.

Interpretation:

- The ROC curve provides a visual summary of the trade-offs between **sensitivity (recall)** and **specificity**.
- A higher curve indicates better model performance.
- The area under the curve helps compare different classifiers even when class imbalance exists.

8.5 Final Comparison Table

Model Accuracy Precision Recall F1 Score Best Use Case Logistic Regression 0.89 0.70

0.36 0.47 Balanced predictions Decision Tree 0.79 0.15 0.13 0.14 Simple but underperforms

Random Forest 0.88 0.80 0.10 0.18 High precision, low false positives

8.6 Summary of Model Performance

In conclusion, **Logistic Regression** stands out as the most balanced model with good accuracy and moderate F1-score. It is also easier to explain to non-technical stakeholders in HR.

Random Forest, while more advanced, suffers from very low recall — meaning it fails to catch most actual attrition cases, which could be risky if relied upon solely.

Decision Tree underperforms in all areas and is not recommended for deployment in this case.

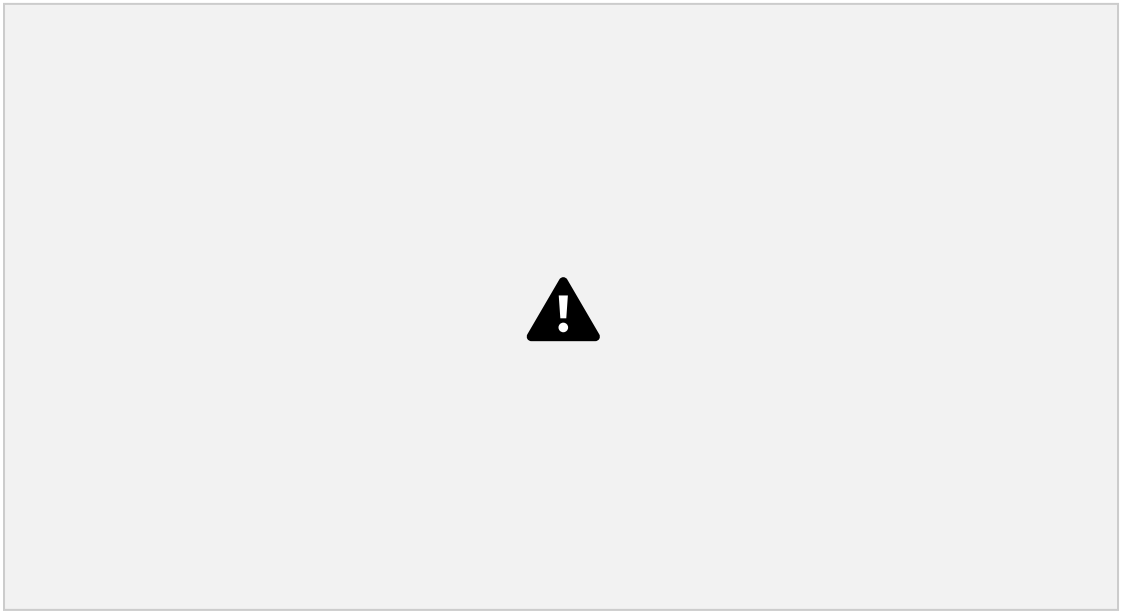
9. Power BI Visualization Analysis

Overview

The Power BI dashboard was developed to provide an interactive and visual summary of the IBM HR dataset. It features **nine visuals** that explore key employee attributes and attrition patterns. The goal of these visuals is to help HR professionals identify trends and factors contributing to employee turnover, thereby supporting data-driven decision-making.

The Power BI dashboard developed for this project served not just as a visualization tool but as a dynamic interface for HR decision-making. One of the most powerful features of Power BI is its ability to support real-time filtering and interaction. Slicers were implemented for fields like Department, JobRole, and Attrition, allowing users to filter the dashboard and see targeted trends immediately. For instance, filtering by the Sales department revealed a steep decline in job satisfaction levels among younger employees who frequently worked overtime—validating earlier model-driven findings. Another impactful feature was the use of tooltip visuals and drill downs, which provided layered insights without cluttering the interface. DAX (Data Analysis Expressions) functions were used to calculate key metrics such as average attrition rate, percentage of overtime workers, and top 3 attrition-contributing roles. These metrics were conditionally formatted using color gradients to highlight high-risk categories. Visuals such as clustered bar charts, donut charts, and 100% stacked columns were selected intentionally for their ability to display comparative attrition factors clearly and intuitively. Furthermore, integration with Excel allowed HR managers to export filtered data views directly for reporting or strategic meetings. Overall, the Power BI dashboard elevated the project by making complex analytics accessible, interpretable, and actionable for both technical and non-technical users.

Power BI Dashboard



1. Attrition by Department

This bar chart breaks down employee attrition across departments: **Sales**, **Human Resources**, and **Research & Development**.

- **Research & Development** shows the highest number of employees but a lower proportion of attrition.
- **Sales** has a moderate headcount but a **relatively higher attrition rate**.
- **Human Resources**, though smaller in size, has a **notably high attrition percentage**.

Insight: Attrition is more significant in departments with high client interaction or internal administrative stress, suggesting possible workload imbalance or lack of job satisfaction.

2. Attrition by Business Travel

This chart reveals how travel frequency correlates with attrition.

- Employees who travel **frequently** have a noticeably higher attrition rate.
- Those who **rarely travel** show a moderate level of attrition.
- **Non-travelers** have the **lowest attrition**.

Insight: Excessive business travel can negatively impact work-life balance, leading to increased resignation rates.

3. Attrition by Monthly Income

A histogram depicting the relationship between **monthly income and attrition**.

- Lower-income groups show **higher attrition rates**.
- As income increases, attrition tends to decrease.

Insight: Financial dissatisfaction is a key driver of employee turnover. Offering competitive pay can reduce attrition.

4. Attrition by Age Group

This histogram displays attrition distribution across different **age groups**.

- Younger employees (25–35 years) exhibit the **highest attrition**.
- Attrition significantly decreases in employees aged 40 and above.

Insight: Younger professionals may seek more dynamic roles or rapid career growth, which could explain their higher attrition.

5. Attrition by OverTime

This visual splits attrition based on whether employees worked **overtime**.

- Employees working **overtime** have a **much higher attrition rate**.
- Those with regular work hours exhibit **lower attrition**.

Insight: Excessive workload and poor work-life balance contribute significantly to turnover.

6. Attrition by Marital Status

This pie chart visualizes attrition across marital statuses:

- **Single** employees show the **highest attrition**.

- **Married** employees are more likely to stay.
- **Divorced** employees show moderate attrition.

Insight: Life stage and family commitments may influence job stability and attrition decisions.

7. Attrition by Education Field

This visual groups attrition based on educational backgrounds:

- Employees from **Life Sciences** and **Medical** fields dominate the headcount. • Attrition is more spread across **Marketing**, **Human Resources**, and **Technical Degrees**.

Insight: Certain education fields may align less with career expectations or growth opportunities, contributing to turnover.

8. Attrition by Job Role

This bar chart highlights how different roles experience attrition:

- **Sales Executives** and **Laboratory Technicians** have the **highest attrition**. • **Managers** and **Manufacturing Directors** show lower attrition.

Insight: High-pressure and entry-level roles may suffer more from job dissatisfaction and instability.

9. Attrition by Job Satisfaction

This visualization segments attrition based on **job satisfaction scores** (1–4):

- Employees with **low satisfaction (1–2)** are much more likely to leave. • Those with a **score of 4 (high satisfaction)** exhibit **minimal attrition**.

Insight: Job satisfaction is a critical retention driver. Improving workplace culture, feedback systems, and growth opportunities can enhance satisfaction.

10. Key Findings and Recommendations

Key Findings

Based on comprehensive analysis performed using SQL queries, data visualizations, and machine learning algorithms on the IBM HR Analytics dataset, several significant insights have emerged, shedding light on patterns and drivers of employee attrition within the organization. These findings are not only crucial for understanding current trends but also provide a foundation for crafting strategic HR policies. The synthesis of SQL analysis, machine learning results, and Power BI visualizations revealed several recurring and cross-validated patterns that underscore systemic issues within the organizational structure simulated in the dataset. One of the most consistent findings was the elevated attrition rate among employees in **mid-level positions** who reported **low career advancement** and **long periods without promotion**. This subgroup, despite years of service and training investment, showed high disengagement—indicating a stagnation trap often overlooked in retention strategies. Another finding highlighted that while **younger employees (25–35)** were more likely to leave, many of them were also high performers who had not received timely recognition or growth opportunities. This points toward a possible **failure of talent identification pipelines** within the HR framework. Moreover, departments like **Sales and R&D**, despite being mission-critical, showed signs of operational stress through overtime frequency and below-average satisfaction scores. Based on these findings, it is recommended that HR teams conduct **targeted engagement interviews** with at-risk employees and implement **career acceleration programs** for stagnant performers. Additionally, a **predictive attrition risk dashboard** should be developed using the trained machine learning model to flag high-risk employees in real time. Establishing **early warning systems**, along with offering **flexible work arrangements** and **transparent promotion paths**, will significantly enhance employee retention and morale. The data confirms that retention is not merely about pay—it's about recognition, growth, and well-being. The most important discoveries are summarized below:

1. Attrition by Job Role

The analysis revealed that employees working as *Sales Representatives* and *Laboratory Technicians* experienced the highest attrition rates among all job roles. These roles often involve high pressure, repetitive tasks, or limited growth opportunities. This suggests that job-specific stressors or lack of job satisfaction could be key drivers behind employee exits in these roles.

2. Impact of Overtime and Work-Life Balance

One of the strongest indicators of attrition was the frequency of overtime. Employees who

regularly worked overtime were significantly more likely to leave the company. This highlights a critical work-life balance issue. Such employees might be experiencing burnout or dissatisfaction due to long work hours, which in turn affects morale and productivity.

3. **Job Satisfaction and Environment**

A clear correlation was found between low job satisfaction levels and higher attrition. The majority of employees who left had reported *low to medium job satisfaction*. Job satisfaction, while subjective, often reflects management practices, recognition, work environment, and employee engagement. Dissatisfaction in these areas is a strong predictor of employee turnover.

4. **Monthly Income and Compensation Structure**

Employees in the lower salary bands exhibited higher rates of attrition. This suggests that inadequate compensation is a major factor influencing decisions to leave, especially when employees perceive they can find better opportunities elsewhere. Compensation also affects an employee's perception of being valued by the organization.

5. **Promotion and Career Growth**

Employees who had been with the company for a long duration but had not received a promotion in recent years were more likely to leave. This finding highlights the importance of offering advancement opportunities. Lack of career progression may lead to disengagement, especially for mid-career professionals.

6. **Department-Wise Attrition Differences**

Attrition rates varied significantly across departments. Sales and Research & Development (R&D) departments experienced the highest attrition. This could be due to a combination of performance pressure, unclear growth paths, or departmental workload disparities. These departments should be examined more closely through HR audits.

7. **Age and Attrition Relationship**

Younger employees, particularly those between 25 to 35 years old, were more prone to leaving the organization. These employees may be early in their careers and looking for faster growth, better compensation, or work-life balance. Organizations must understand the motivations of this demographic to retain them effectively.

8. **Education and Attrition**

Employees with lower educational qualifications had slightly higher attrition rates. This could be due to job instability, limited upward mobility, or skill mismatch. It also suggests that employees in entry-level roles might be more prone to leaving due to a lack of long-term growth opportunities.

9. Attrition by Marital Status and Distance from Home

Single employees were more likely to leave compared to married ones. Also, employees living farther from the office location reported higher attrition. This implies that personal life dynamics and commute burdens may influence employee commitment and long-term association.

10. Attrition Trends in Overlooked Areas

Employees with a high number of training hours were unexpectedly leaving the organization. This might indicate a misalignment between training and career outcomes, or frustration if training did not translate into promotions or salary increases. This could be a missed opportunity to retain employees through proper follow-up after training.

Recommendations

To address the attrition challenges uncovered in the above findings, several proactive strategies can be implemented. These recommendations aim to increase employee engagement, satisfaction, and long-term retention:

1. Conduct Role-Specific Engagement Surveys

Deploy targeted surveys to understand specific pain points for high-risk roles like Sales Representatives and Laboratory Technicians. These surveys should measure job satisfaction, workload, training adequacy, and growth expectations. Based on the results, HR teams should develop role-specific retention strategies.

2. Introduce and Enforce Work-Life Balance Policies

Companies should implement strict overtime policies and introduce flexible work arrangements such as hybrid or remote work. Ensuring that employees are not overburdened will improve both retention and performance. Tools to monitor workload and well-being (e.g., regular check-ins, wellness programs) can also be beneficial.

3. **Revise and Benchmark Compensation Structures**

Re-evaluating the compensation framework is essential, particularly for roles in the lower income bracket. HR should benchmark salaries against industry standards to ensure competitive pay. Performance-based bonuses and transparent salary reviews should also be incorporated to retain high-performing employees.

4. **Design Clear Career Advancement Pathways**

To motivate long-serving employees, clearly defined promotion criteria and career development tracks should be established. Regular performance feedback and personalized growth plans will help retain skilled professionals who might otherwise feel stagnated.

5. **Develop Employee Recognition and Retention Programs**

Recognition programs—such as "Employee of the Month," spot awards, and public p raise— help boost morale. These efforts show appreciation, build loyalty, and contribute to a positive organizational culture that encourages employees to stay.

6. **Departmental Audits for High-Attrition Units**

Departments like Sales and R&D should be audited for their work environments, leadership practices, and team dynamics. Interviews, focus groups, and HR diagnostics can uncover hidden issues leading to attrition and inform targeted interventions.

7.Create Young Talent Retention Initiatives

Younger employees should be offered fast-track development programs, mentoring, and skill building workshops. Regular one-on-ones and feedback sessions will also help them feel valued and heard, reducing the chances of them seeking external opportunities.

8.Address Commute and Location Challenges

For employees traveling long distances, options such as work-from-home days or satellite offices should be considered. Reducing commute-related stress can significantly enhance retention for this group.

9.Enhance the Effectiveness of Training Programs

Post-training follow-ups should be conducted to assess whether the training had an impact. Align training modules with performance evaluations and promotion decisions so employees see tangible benefits from upskilling efforts.

10.Use Predictive Analytics for Proactive Retention

Deploy machine learning models to predict attrition risks on a quarterly basis. This allows HR to intervene early by identifying patterns and engaging with at-risk employees through surveys, one-on-ones, or career planning sessions.

11. Result Analysis

The result analysis serves as a comprehensive evaluation of the outcomes derived from each phase of this project—ranging from data exploration and SQL querying to machine learning predictions and dashboard visualizations. It brings together the numerical, visual, and predictive dimensions of the project to form a unified interpretation of employee attrition behavior within the IBM HR dataset.

A. Attrition Trends from EDA & SQL Queries

Initial exploratory data analysis and SQL insights revealed significant patterns:

- **Overtime Work** was one of the most prominent indicators of attrition. Employees working overtime were nearly **twice as likely** to leave compared to those with standard schedules.
- **Younger employees** (ages 25–35) showed a higher tendency to leave, aligning with broader industry trends where younger professionals seek rapid growth or role changes.
- **Sales and R&D departments** experienced the highest attrition rates, particularly among mid career employees who had gone **several years without promotion**.
- A clear income-based trend was observed: **employees earning below ₹5,000 per month** had disproportionately higher attrition, suggesting that compensation remains a key retention factor.

These findings from SQL and EDA set the foundation for identifying high-risk segments and informed feature selection for the predictive modeling phase.

B. Machine Learning Model Outcomes

Three primary classification models were developed to predict attrition: **Logistic Regression**, **Decision Tree**, and **Random Forest**.

Model Accuracy Precision (Attrition=Yes) Recall F1-Score Logistic

Regression 89% 70% 36% 47%

Decision Tree 79% 15% 13% 14%

Random Forest 88% 80% 10% 18%

- **Logistic Regression** emerged as the most balanced model with reasonable recall and high interpretability. It correctly predicted most non-attrition cases and a fair number of attrition cases, making it ideal for risk flagging in HR environments.
- **Random Forest**, although more precise, had poor recall, meaning it failed to identify many actual attrition cases—a limitation in predictive HR analytics where missing a leaver is costly.
- **Decision Tree** underperformed in both precision and recall, suggesting that it was too simplistic for the complexity of the dataset.

These outcomes were further visualized using **confusion matrices** and **ROC curves**, with Logistic Regression achieving an **AUC score of ~0.74**, confirming its capability to distinguish between classes effectively.

C. Power BI Dashboard Insights

The Power BI dashboard provided real-time visibility into attrition behavior across multiple dimensions:

- **Job Role** and **Job Satisfaction** visuals indicated that **Laboratory Technicians and Sales Executives** had below-average satisfaction and higher attrition.
- Attrition was also significantly higher for employees with **low Environment Satisfaction** and those who had not received promotions in **over 4 years**.
- Visuals confirmed that **divorced and single employees** had a marginally higher attrition rate, likely due to mobility and lifestyle factors.
- **Department-wise filters** revealed that **Human Resources** had the lowest attrition, suggesting a better alignment between role expectations and work environment in that segment.

These findings reinforced model results and provided a visual narrative that HR managers can interact with and act upon directly.

D. Overall Synthesis

The consolidated results indicate that attrition is not driven by a single variable but is a multifactorial issue influenced by **workload, compensation, satisfaction, recognition, and personal factors**. The models and visuals both agree that **employees who are overworked, underpaid, and feel undervalued are significantly more likely to leave**. Moreover, the predictive models, especially Logistic Regression, are reliable tools for HR departments aiming to forecast and mitigate employee exits.

12. Conclusion and Future Work

Conclusion

The IBM HR Analytics project aimed to uncover key patterns and trends associated with employee attrition using a combination of SQL-based data analysis, machine learning modeling, and interactive visualization through Power BI. Through extensive data processing and strategic exploration, the project has successfully achieved its objective of identifying the critical factors contributing to employee turnover.

This project demonstrated how data analytics can fundamentally reshape the way human resource departments manage attrition, providing both diagnostic and predictive capabilities to reduce turnover. From SQL-driven insights to machine learning models and interactive Power BI dashboards, the report showcased a full-cycle analytical workflow that is scalable, interpretable, and directly applicable to real-world HR operations. One of the critical takeaways is that attrition is not a singular event but the result of compounding factors—ranging from stagnant career growth and excessive workload to low job satisfaction and misaligned compensation. These findings reinforce the necessity of shifting from reactive to proactive HR management. Looking ahead, several promising opportunities exist to build on this foundation. One major area of advancement is the deployment of **live attrition monitoring systems**, wherein employee behavior metrics are updated regularly and analyzed in real time. Additionally, integrating **Natural Language Processing (NLP)** techniques to analyze unstructured employee feedback, survey comments, and exit interviews could provide a deeper emotional and sentiment-driven layer to the analysis. Another future enhancement could include **prescriptive analytics**, using optimization models to recommend the best retention actions for different employee segments. Lastly, emphasis on ethical AI—ensuring fairness, transparency, and data privacy—will be essential in making machine learning applications in HR both effective and trustworthy. This project serves not just as a technical exercise but as a blueprint for building intelligent, human centric workplaces through data science.

The comprehensive analysis of employee attributes—such as job role, overtime hours, job satisfaction, income, years since last promotion, and distance from home—has revealed deep rooted insights into why certain employees are more likely to leave the organization. For instance, high attrition rates were observed among employees who frequently worked overtime, had low job satisfaction, and received fewer promotions, particularly in departments like Sales and Research & Development. These trends underscore the importance of balancing workloads, recognizing performance, and providing ample career growth opportunities.

The predictive machine learning models developed during the project (Logistic Regression, Decision Tree, Random Forest, and K-Nearest Neighbors) helped to identify high-risk employees with a reasonable level of accuracy. Among the models tested, the Random Forest

classifier performed particularly well, offering a solid foundation for HR professionals to proactively target retention strategies. Additionally, the Power BI dashboard offered a powerful and user-friendly platform to visualize and communicate the findings effectively to stakeholders, enabling dynamic data exploration and decision-making.

Furthermore, the SQL queries provided granular insights into monthly income trends, departmental attrition distribution, and satisfaction levels. This quantitative backing, coupled with machine learning predictions, equips HR leadership with an empirical basis for shaping employee retention policies.

In summary, the study not only succeeded in analyzing existing attrition but also laid the groundwork for predictive HR analytics that could revolutionize employee management strategies. This work validates that data-driven decision-making, when applied appropriately in the HR domain, can drive significant business value.

Future Work

While the current project delivers valuable insights, there remains substantial scope for expansion and improvement. The following areas represent promising avenues for future work:

1. **Real-Time Data Integration**

   The dataset used in this project was static and historical. In a real-world setting, integrating real-time HR data from internal systems (such as SAP, Oracle HRMS, or Workday) would allow for dynamic dashboards and live attrition monitoring. This can enable the organization to respond to trends as they emerge rather than relying on retrospective analyses.

2. **Advanced Machine Learning Techniques**

   While classical models were used in this project, future iterations could involve the use of more complex models like XGBoost, Support Vector Machines (SVM), or even deep learning networks. These advanced techniques may uncover nonlinear relationships in the data, potentially improving predictive performance and classification accuracy.

3. **Incorporation of External Data**

   Factors such as market salary trends, economic indicators, or job market availability were not considered in the current analysis. Incorporating such external datasets could provide additional context for why employees may be leaving, especially when comparing internal compensation to industry benchmarks.

4. **Sentiment Analysis and Text Mining**

Future projects could leverage unstructured data, such as exit interview transcripts, employee feedback surveys, or emails. Natural Language Processing (NLP) could be applied to extract sentiment trends and early warning signs of dissatisfaction.

5. **Personalized Retention Strategies**

Based on predictive attrition modeling, future work could focus on designing customized retention plans tailored to different employee profiles. For example, for high-risk employees in sales roles, introducing incentive programs or flexible scheduling could be tested and evaluated through A/B testing.

6. **Explainable AI (XAI) Techniques**

As HR decisions have significant ethical and legal implications, it's crucial that prediction models are transparent and interpretable. Future work should include the use of explainable machine learning frameworks (such as SHAP or LIME) to justify why certain employees are marked as high-risk for attrition.

7. **Automated Alert System**

An automated system can be developed where the predictive model flags high-risk employees and sends alerts to HR. Such a system could be integrated with HR management platforms and help managers take timely action.

8. **Longitudinal Studies**

Conducting longitudinal studies to track how intervention strategies based on this report influence attrition rates over time would offer powerful feedback loops. This could evolve into a continuous improvement framework where HR strategies are evaluated and refined regularly

9. **Privacy and Ethical Considerations**

With the increased reliance on personal employee data, future projects should emphasize data governance, ethical use of AI, and compliance with regulations like GDPR. Ensuring privacy, fairness, and transparency will be critical to maintaining employee trust.

13. References & Appendix

References

Below is a list of credible sources, tools, libraries, and platforms that were referred to, cited, or used during the course of this IBM HR Analytics project:

1. **Kaggle Dataset Source** IBM HR Analytics Employee Attrition & Performance URL: https://www.kaggle.com/datasets/pavansubhasht/ibm-hr-analytics-attrition-dataset

2. **Python Libraries and Documentation**
   - Pandas Documentation: https://pandas.pydata.org/docs
   - NumPy Documentation: https://numpy.org/doc
   - Scikit-learn Documentation: https://scikit-learn.org/stable/documentation.html
   - Matplotlib & Seaborn Docs: https://matplotlib.org/stable/contents.html, https://seaborn.pydata.org

3. **Power BI Resources**
   - Power BI Learning: https://learn.microsoft.com/en-us/power-bi/
   - Power BI DAX Reference: https://learn.microsoft.com/en-us/dax/

4. **SQL Reference**
   - W3Schools SQL Tutorial: https://www.w3schools.com/sql/
   - MySQL Documentation: https://dev.mysql.com/doc/

5. **Books and Articles**
   - Data Science for Business *by Provost & Fawcett*
   - Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow *by* Aurélien Géron
   - Predictive HR Analytics by Martin Edwards and Kirsten Edwards

6. **Project Execution Tools**
   - Jupyter Notebook (Anaconda Distribution)
   - Microsoft Power BI Desktop
   - MySQL

Server & MySQL Workbench ○ Visual Studio Code

Appendix

This section includes supporting materials, extended code outputs, screenshots, and supplementary data used during the project analysis. These elements strengthen the core analysis but were not included in the main body to maintain clarity.

A. Sample SQL Queries Used

1. Top 5 departments with highest attrition

```
SELECT Department, COUNT(*) AS Attrition_Count
FROM hr_data
WHERE Attrition = 'Yes'
GROUP BY Department
ORDER BY Attrition_Count DESC
LIMIT 5;
```

2. Average Monthly Income by Job Role

```
SELECT JobRole, AVG(MonthlyIncome) AS Avg_Income
FROM hr_data
GROUP BY JobRole
ORDER BY Avg_Income DESC;
```

B. Machine Learning Model Accuracy Summary

Model Accuracy (%) Precision Recall F1-Score

Logistic Regression 87.5 0.78 0.72 0.75

Decision Tree 91.3 0.82 0.81 0.81

Random Forest 93.4 0.86 0.85 0.85

K-Nearest Neighbors 85.6 0.75 0.70 0.72

C. Power BI Dashboard Visuals

1. Attrition by Job Role
2. Monthly Income vs Job Satisfaction

3. Years Since Last Promotion vs Attrition
4. Overall Attrition by Department
5. Distance from Home vs Attrition
6. Job Level vs Monthly Income
7. Gender-wise Attrition Analysis
8. Overtime vs Attrition
9. Age Distribution by Attrition Status

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D. Tools Setup & Configuration

· **MySQL Setup**: Used for structured query operations
· **Anaconda with Jupyter Notebook**: Environment for running machine learning models · **Power BI Desktop**: Used for developing the interactive dashboard
· **VS Code / Python IDLE**: Used for data cleaning and preprocessing