

Report: Data Preprocessing and Machine Learning Model

Evaluation:

I. 1. Introduction

Employee attrition, or employee turnover, is a significant concern for many organizations as it can lead to substantial costs in terms of recruitment, training, and loss of productivity. Understanding and predicting which employees are likely to leave the company can help organizations take proactive steps to improve employee retention, thereby saving costs and maintaining a stable workforce.

This project focuses on predicting employee attrition using a machine learning approach. We aim to build a predictive model that can identify employees at risk of leaving the company based on various features such as demographic information, job role, work environment, and personal factors.

The dataset used for this project is the HR Employee Attrition dataset, which contains information on 2940 employees, including their age, business travel frequency, department, distance from home, education, job role, job satisfaction, and many other factors.

The tasks performed in this project can be categorized into two main parts:

Data Preprocessing and Cleaning:

- Data Exploration: Analyzing the dataset to understand its structure and identify important features.
- Data Cleaning: Handling missing values, removing duplicates, and addressing any inconsistencies in the data.
- Data Encoding: Converting categorical variables into a format suitable for machine learning algorithms.
- Data Standardization: Scaling numerical features to ensure they contribute equally to the model.

Building Machine Learning Models:

- Model Training: Training a logistic regression model to predict employee attrition.
- Model Evaluation: Evaluating the model's performance using metrics such as accuracy, confusion matrix, precision, recall, and F1-score.

By the end of this project, we aim to have a robust predictive model that can help HR departments identify at-risk employees and take necessary actions to improve retention. The insights gained from this model can also guide organizations in making

data-driven decisions to enhance employee satisfaction and reduce turnover rates.

I. Data Preprocessing and Cleaning

a. data exploration:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score

# Load the data
df = pd.read_csv('C:/Users/4B/Downloads/WA_Fn-UseC_HR-Employee-Attrition (1).csv')

# Data exploration
print("First rows of the data:")
print(df.head())
print("\nDescription of the data:")
print(df.describe())
print("\nInformation about the data:")
print(df.info())
```

b. Cleaning data:

```
# Data cleaning: check for missing values
print("\nMissing values per column:")
print(df.isnull().sum())
```

c. data encoding:

```
# Encoding the target variable 'Attrition'
df['Attrition'] = df['Attrition'].map({'Yes': 1, 'No': 0})

# Splitting features and target
X = df.drop('Attrition', axis=1)
y = df['Attrition']

# Identifying numeric and categorical columns
numeric_features = X.select_dtypes(include=[int, float]).columns
categorical_features = X.select_dtypes(include=[object]).columns

# Label Encoding categorical variables (before One-Hot Encoding for checking)
for col in categorical_features:
    X[col] = LabelEncoder().fit_transform(X[col])

# One-Hot Encoding categorical variables
X = pd.get_dummies(X, columns=categorical_features)
```

d. data Standardization:

```
# Standardizing numeric features
scaler = StandardScaler()
X[numeric_features] = scaler.fit_transform(X[numeric_features])
```

II. Building Machine Learning Models

```
# Splitting data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

# Training a Logistic regression model
model = LogisticRegression(max_iter=1000)
model.fit(X_train, y_train)

# Predictions and model evaluation
y_pred = model.predict(X_test)

print("Accuracy:", accuracy_score(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
```

IV. Execution

```
Premières lignes des données :
   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

   DistanceFromHome   Education   EducationField   EmployeeCount   EmployeeNumber \
0                1          2   Life Sciences           1             1
1                8          1   Life Sciences           1             2
2                2          2      Other              1             4
3                3          4   Life Sciences           1             5
4                2          1    Medical              1             7

... RelationshipSatisfaction   StandardHours   StockOptionLevel \
0 ...                1             80             0
1 ...                4             80             1
```

2	...	2	80	0
3	...	3	80	0
4	...	4	80	1

	TotalWorkingYears	TrainingTimesLastYear	WorkLifeBalance	YearsAtCompany \
0	8		0	1
1	10		3	3
2	7		3	3
3	8		3	3
4	6		3	3

	YearsInCurrentRole	YearsSinceLastPromotion	YearsWithCurrManager
0	4	0	5
1	7	1	7
2	0	0	0
3	7	3	0
4	2	2	2

[5 rows x 35 columns]

Description des données :

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount \
count	1470.000000	1470.000000	1470.000000	1470.000000	1470.0
mean	36.923810	802.485714	9.192517	2.912925	1.0
std	9.135373	403.509100	8.106864	1.024165	0.0
min	18.000000	102.000000	1.000000	1.000000	1.0
25%	30.000000	465.000000	2.000000	2.000000	1.0
50%	36.000000	802.000000	7.000000	3.000000	1.0
75%	43.000000	1157.000000	14.000000	4.000000	1.0
max	60.000000	1499.000000	29.000000	5.000000	1.0

	EmployeeNumber	EnvironmentSatisfaction	HourlyRate	JobInvolvement \
count	1470.000000	1470.000000	1470.000000	1470.000000
mean	1024.865306	2.721769	65.891156	2.729932
std	602.024335	1.093082	20.329428	0.711561
min	1.000000	1.000000	30.000000	1.000000

25%	491.250000	2.000000	48.000000	2.000000
50%	1020.500000	3.000000	66.000000	3.000000
75%	1555.750000	4.000000	83.750000	3.000000
max	2068.000000	4.000000	100.000000	4.000000

	JobLevel	...	RelationshipSatisfaction	StandardHours \
count	1470.000000	...	1470.000000	1470.0
mean	2.063946	...	2.712245	80.0
std	1.106940	...	1.081209	0.0
min	1.000000	...	1.000000	80.0
25%	1.000000	...	2.000000	80.0
50%	2.000000	...	3.000000	80.0
75%	3.000000	...	4.000000	80.0
max	5.000000	...	4.000000	80.0

	StockOptionLevel	TotalWorkingYears	TrainingTimesLastYear \
count	1470.000000	1470.000000	1470.000000
mean	0.793878	11.279592	2.799320

std	0.852077	7.780782	1.289271
min	0.000000	0.000000	0.000000
25%	0.000000	6.000000	2.000000
50%	1.000000	10.000000	3.000000
75%	1.000000	15.000000	3.000000
max	3.000000	40.000000	6.000000

	WorkLifeBalance	YearsAtCompany	YearsInCurrentRole \
count	1470.000000	1470.000000	1470.000000
mean	2.761224	7.008163	4.229252
std	0.706476	6.126525	3.623137
min	1.000000	0.000000	0.000000
25%	2.000000	3.000000	2.000000
50%	3.000000	5.000000	3.000000
75%	3.000000	9.000000	7.000000
max	4.000000	40.000000	18.000000

	YearsSinceLastPromotion	YearsWithCurrManager
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count	1470.000000	1470.000000
mean	2.187755	4.123129
std	3.222430	3.568136
min	0.000000	0.000000
25%	0.000000	2.000000
50%	1.000000	3.000000
75%	3.000000	7.000000
max	15.000000	17.000000

[8 rows x 26 columns]

Information sur les données :

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 1470 entries, 0 to 1469

Data columns (total 35 columns):

#	Column	Non-Null Count	Dtype
0	Age	1470 non-null	int64

1	Attrition	1470 non-null	object
2	BusinessTravel	1470 non-null	object
3	DailyRate	1470 non-null	int64
4	Department	1470 non-null	object
5	DistanceFromHome	1470 non-null	int64
6	Education	1470 non-null	int64
7	EducationField	1470 non-null	object
8	EmployeeCount	1470 non-null	int64
9	EmployeeNumber	1470 non-null	int64
10	EnvironmentSatisfaction	1470 non-null	int64
11	Gender	1470 non-null	object
12	HourlyRate	1470 non-null	int64
13	JobInvolvement	1470 non-null	int64
14	JobLevel	1470 non-null	int64
15	JobRole	1470 non-null	object
16	JobSatisfaction	1470 non-null	int64
17	MaritalStatus	1470 non-null	object
18	MonthlyIncome	1470 non-null	int64

19	MonthlyRate	1470 non-null	int64
20	NumCompaniesWorked	1470 non-null	int64
21	Over18	1470 non-null	object
22	OverTime	1470 non-null	object
23	PercentSalaryHike	1470 non-null	int64
24	PerformanceRating	1470 non-null	int64
25	RelationshipSatisfaction	1470 non-null	int64
26	StandardHours	1470 non-null	int64
27	StockOptionLevel	1470 non-null	int64
28	TotalWorkingYears	1470 non-null	int64
29	TrainingTimesLastYear	1470 non-null	int64
30	WorkLifeBalance	1470 non-null	int64
31	YearsAtCompany	1470 non-null	int64
32	YearsInCurrentRole	1470 non-null	int64
33	YearsSinceLastPromotion	1470 non-null	int64
34	YearsWithCurrManager	1470 non-null	int64

dtypes: int64(26), object(9)

memory usage: 402.1+ KB

None

Valeurs manquantes par colonne :

Age	0
Attrition	0
BusinessTravel	0
DailyRate	0
Department	0
DistanceFromHome	0
Education	0
EducationField	0
EmployeeCount	0
EmployeeNumber	0
EnvironmentSatisfaction	0
Gender	0
HourlyRate	0
JobInvolvement	0
JobLevel	0

JobRole	0
JobSatisfaction	0
MaritalStatus	0
MonthlyIncome	0
MonthlyRate	0
NumCompaniesWorked	0
Over18	0
OverTime	0
PercentSalaryHike	0
PerformanceRating	0
RelationshipSatisfaction	0
StandardHours	0
StockOptionLevel	0
TotalWorkingYears	0
TrainingTimesLastYear	0
WorkLifeBalance	0
YearsAtCompany	0
YearsInCurrentRole	0

```
YearsAtCompany      0
YearsInCurrentRole  0
YearsSinceLastPromotion  0
YearsWithCurrManager  0
dtype: int64
Accuracy: 0.891156462585034
Confusion Matrix:
[[244  11]
 [ 21  18]]
Classification Report:
              precision    recall  f1-score   support

      0       0.92       0.96       0.94        255
      1       0.62       0.46       0.53         39

   accuracy          0.89        294
  macro avg       0.77       0.71       0.73        294
 weighted avg       0.88       0.89       0.88        294
```

Conclusion:

In this project, we utilized machine learning to predict employee attrition, a crucial issue impacting organizational costs and stability. By preprocessing and cleaning the data, encoding categorical variables, and standardizing numerical features, we prepared the dataset for modeling. A logistic regression model was then trained and evaluated, achieving an accuracy of 89.12%. This predictive model equips HR departments with valuable insights to identify at-risk employees and implement targeted retention strategies. The results underscore the potential of data-driven approaches in enhancing workforce management and decision-making processes within organizations.

