



A

Assessment Report

on

"Predict Employee Attrition"

submitted as partial fulfillment for the award of

BACHELOR OF TECHNOLOGY DEGREE

SESSION 2024-25

in

Introduction to AI

By

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May, 2025

Introduction

Problem Statement: Build a classification model to predict whether an employee is likely to leave the company based on features like job satisfaction, salary, work environment, and years of experience. The prediction can help companies focus their efforts on employee retention strategies.

Employee attrition poses a significant challenge for businesses, as it leads to higher recruitment costs and a loss of experienced talent. Predicting employee turnover can help organizations take proactive steps in retaining valuable employees, optimizing recruitment efforts, and improving overall workforce stability. This project aims to build a predictive machine learning model to identify employees who are at risk of leaving the company based on various factors, including job satisfaction, salary, work environment, and years of experience. By doing so, companies can implement targeted interventions to retain top talent and reduce attrition rates.

Methodology

The approach to solving this problem involves several key steps, as outlined below:

1. Data Collection

The dataset used in this project contains various features that describe employee characteristics, including job satisfaction, monthly income, work environment satisfaction, and tenure with the company. This data was uploaded in CSV format and serves as the foundation for the predictive model.

2. Data Preprocessing

- Handling Irrelevant Features: Certain columns, such as 'EmployeeCount', 'EmployeeNumber', 'Over18', and 'StandardHours', were dropped from the dataset, as they were not relevant to predicting employee attrition.
- Encoding Categorical Data: Categorical variables, including job roles and departments, were encoded into numerical values using LabelEncoder. This transformation enables the use of these variables in machine learning models.

3. Feature Selection

Key features that are likely to influence employee attrition were selected for the model. These include:

- Job satisfaction
- Monthly income
- Environment satisfaction
- Work-life balance
- Total working years
- Years at the company
 These features were chosen based on their relevance and potential impact on employee turnover.

4. Model Selection and Training

A Random Forest Classifier was chosen due to its ability to handle both numerical and categorical data efficiently. Random Forests are robust, capable of capturing complex patterns, and provide reliable performance with minimal parameter tuning. The dataset was split into an 80% training set and a 20% testing set to train the model and evaluate its performance.

5. Model Evaluation

- The model's performance was assessed using several evaluation metrics:
 - Accuracy: The percentage of correct predictions.
 - Precision: The proportion of true positives among the predicted positives.
 - Recall: The proportion of true positives among all actual positives.
- Additionally, a confusion matrix was generated to visualize the model's performance, showing the number of true positives, true negatives, false positives, and false negatives.

CODE

```
Importing required libraries
 import pandas as pd
 import seaborn as sns
  import matplotlib.pyplot as plt
 from sklearn.model_selection import train_test_split
 from sklearn.preprocessing import LabelEncoder
                                                                                    # For encoding categorical variables into numbers
# For creating a Random Forest classification model
from sklearn.ensemble import RandomForestclassifier # For creating a Random Forest classification model from sklearn.entrics import confusion_matrix, accuracy_score, precision_score, recall_score # For model evaluation
 from google.colab import files
# 2. Uploading the CSV file

print(" Please upload your dataset CSV file:") # Prompt user to upload file

uploaded = files.upload() # Opens file uploader dialog in Google Colab
        Reading the uploaded file into a DataFrame
 for file_name in uploaded.keys():
     df = pd.read_csv(file_name)
# 4. Dropping irrelevant columns if present

irrelevant_columns = ['EmployeeCount', 'EmployeeNumber', 'Over18', 'StandardHours'] # Columns not useful for predicti

df.drop(columns=[col for col in irrelevant_columns if col in df.columns], inplace=True) # Drop those columns safely
       Encoding categorical variables
 \begin{array}{l} \textbf{label\_encoders} = \{ \overline{\textbf{j}} \\ \textbf{# Dictionary to store encoders} \  \, \text{for each column} \\ \textbf{for col in df.select\_dtypes(include='object').columns:} \  \, \textbf{# Loop through categorical columns} \\ \end{array} 
      le = LabelEncoder()
      df[col] = le.fit_transform(df[col])
      label_encoders[col] = le
  6. Selecting important features for prediction
selected_features = [
        'JobSatisfaction',
      'MonthlyIncome',
'EnvironmentSatisfaction',
       'TotalWorkingYears',
'YearsAtCompany'
                                                                            # Total working experience in years
# Number of years in current company
 X = df[selected_features]
```

```
# 7. 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_state=42) # 88% train, 28% test

# 8. Training a Random Forest Classifier

model = RandomForestClassifier(random_state=42) # Create a Random Forest model

model_fit(X_train, y_train) # Train the model using training data

# 9. Making predictions on test data

y_pred = model_predict(X_test) # Predict attrition on unseen (test) data

# 10. Evaluating the model

accuracy = accuracy_score(y_test, y_pred) # Calculate the accuracy score

precision = precision_score(y_test, y_pred) # Calculate precision: TP / (TP + PN)

# 11. Creating and displaying confusion matrix heatmap

cm = confusion_matrix(y_test, y_pred) # Calculate recall: TP / (TP + PN)

# 11. Creating and displaying confusion matrix heatmap

plt.figure(figsize=(6, 4)) # Cenerate confusion matrix from predictions

plt.figure(figsize=(6, 4)) # Set y_axis labels

plt.title("Confusion Matrix Heatmap") # Add title

plt.xlabel("Predicted") # Label for x_axis

plt.tight_layout() # Adjust layout to avoid overlap

plt.show() # Display the plot

# 12. Printing final evaluation results

print(" Accuracy: {accuracy + 160:.2f}X") # Display accuracy in percentage

# Display recall in percentage

# Display recall in percentage

# Display recall in percentage
```

OUTPUT

