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**Final Milestone**

**Predicting Employee Attrition Using Machine Learning**

**1. Introduction**

**Problem Statement:**  
Employee attrition is a significant challenge for organizations, especially in sectors with high turnover rates. High attrition rates not only impact team cohesion and morale but also incur substantial costs related to recruiting, training, and loss of productivity. By predicting employee attrition, organizations can proactively address retention risks, allocate resources more effectively, and support employee engagement. Industry research suggests that the average cost of replacing an employee can be up to 33% of their annual salary, highlighting the financial implications of high attrition rates.

**Importance and Usefulness of Solving the Problem:**  
This project aims to develop a predictive model to identify at-risk employees, providing HR teams with a strategic tool to anticipate turnover. Predicting which employees are likely to leave allows HR departments to intervene with targeted retention strategies, reducing turnover costs and preserving valuable institutional knowledge.

**Stakeholder Pitch:**  
For HR leaders and executive management, implementing a predictive attrition model represents a significant investment in workforce stability. This model can help pinpoint factors influencing attrition, enabling the development of tailored retention initiatives. By providing early warning indicators, the model empowers HR to support long-term engagement, ultimately driving down attrition-related costs and improving overall employee satisfaction.

**Data Source:**  
The dataset, “HR Employee Attrition,” was obtained from a popular online repository. It includes demographic information, job role, satisfaction scores, and compensation details for each employee. This dataset was ideal for our analysis, as it included attributes essential to understanding employee turnover behaviors. However, the data had some limitations, such as class imbalance and possible biases in feature representations.

**2. Summary of Milestones 1-3**

**Milestone 1: Exploratory Data Analysis (EDA)**  
We began by performing a comprehensive EDA to identify patterns in the data related to attrition. Key visualizations included:

* **Attrition by Department:** Visualized the attrition rate across departments, revealing higher rates in the sales department.
* **Impact of Job Satisfaction:** Showed a correlation between lower job satisfaction and higher attrition rates, reinforcing job satisfaction as a key predictive factor.
* **Income Disparities:** Highlighted how income level influenced attrition, with lower income groups displaying higher turnover.

These visualizations helped us better understand the factors influencing attrition and informed our feature selection for model training.

**Milestone 2: Data Preparation**  
The data preparation process involved multiple steps:

* **Dropping Irrelevant Features:** We removed columns such as EmployeeCount, EmployeeNumber, and StandardHours, as they had no predictive value for attrition.
* **Handling Missing Values:** Missing numerical values were filled with medians, and categorical values were filled with mode to retain as much data as possible.
* **Encoding Categorical Features:** Dummy variables were created for categorical columns (e.g., job role, marital status) to allow for efficient model processing.

By the end of this stage, our dataset was fully prepared for model training.

**Milestone 3: Model Selection and Evaluation**  
For our predictive task, we experimented with multiple models:

1. **Logistic Regression** was selected for its interpretability and efficiency in binary classification tasks.
2. **Random Forest** was evaluated due to its robustness to overfitting and ability to handle feature interactions.
3. **Decision Tree** was tested as a baseline for comparison, given its simplicity.

Each model was evaluated using accuracy, precision, recall, and AUC-ROC scores to gauge performance. Logistic Regression performed best overall, balancing accuracy and interpretability.

**3. Model Results and Analysis**

**Primary Model - Logistic Regression**  
Logistic Regression achieved an accuracy of 88%, with an AUC-ROC score of 0.79, indicating good discrimination between employees likely to leave and those likely to stay. The confusion matrix showed that the model was successful in identifying non-attrition cases but showed lower recall in predicting true attrition cases. These results suggest that while the model is effective in identifying stable employees, refinement may be needed to capture attrition cases more accurately.

**Alternative Models - Random Forest and Decision Tree**  
The Random Forest model achieved comparable accuracy but exhibited a lower recall score, while the Decision Tree model was prone to overfitting, as indicated by a higher RMSE and negative R^2 score. Although these models provided insights, Logistic Regression was ultimately chosen for its simplicity, performance, and interpretability.

**Challenges and Considerations**  
Our primary challenges included class imbalance and selecting the right evaluation metric. To mitigate class imbalance, we could implement class weighting or resampling techniques in future iterations. Moreover, we found that while accuracy was high, recall scores highlighted areas for improvement in identifying at-risk employees.

**4. Conclusion and Recommendations**

**Summary of Insights**  
The analysis revealed several predictors of attrition, including job satisfaction, income level, and department. These insights can help HR teams prioritize interventions for at-risk employees, targeting job satisfaction and compensation strategies.

**Deployment Readiness**  
The model shows promising results and could be deployed in a controlled environment, such as within an HR dashboard for real-time monitoring. To maintain performance, it would be important to periodically retrain the model with updated data, reflecting any shifts in workforce trends.

**Recommendations for Future Development**  
Future improvements could include the integration of additional data sources, such as employee feedback and performance reviews, to enrich the dataset. Furthermore, implementing regular retraining and monitoring metrics like recall could enhance model efficacy. To address limitations in recall, experimenting with other algorithms, such as Gradient Boosting, could also be beneficial.

**5. Ethical Considerations**

**Bias and Fairness**  
Model predictions could introduce bias, especially if demographic features like age or gender influence predictions. To mitigate this, fairness audits should be conducted to ensure equitable treatment across different employee demographics.

**Transparency**  
To maintain trust, it is important that the model’s predictions are explainable to HR professionals. Simplified model outputs and visualization of feature importance can help make the model accessible and transparent.

**Privacy and Confidentiality**  
Given the sensitive nature of HR data, ensuring data privacy and confidentiality is essential. Access to the model should be restricted to authorized HR personnel, and data should be anonymized where possible.

**References**

Pavansubhash (2016). “IBM HR Analytics Employee Attrition & Performance” [Data set]. Kaggle. https://www.kaggle.com/datasets/pavansubhasht/ibm-hr-analytics-attrition-dataset