PACE UNIVERSITY

Name: Amey Suresh Borkar ; Student ID: AB70967N

<u>Literature Review</u>

Predicting Employee Job Switch:

An Attrition Forecasting Model

Literature Review

1. Introduction:

Employee attrition is a significant challenge for organizations, leading to high recruitment costs, loss of institutional knowledge, and disruptions in workforce stability. Predicting employee job switches enables companies to take proactive measures in retaining key talent and improving organizational efficiency. The emergence of machine learning (ML) techniques has enhanced the ability to forecast employee attrition with higher accuracy than traditional statistical models. This literature review explores existing research in employee turnover prediction, identifies gaps, and highlights the unique contributions of this project.

2. Theoretical Background:

Several established theories provide insight into employee attrition. Herzberg's Two-Factor Theory (1959) differentiates between motivators (e.g., career growth, recognition) and hygiene factors (e.g., salary, work conditions) that influence job satisfaction.

The Job Embeddedness Theory (2001) posits that an employee's likelihood of staying depends on the strength of their professional and personal connections within an organization. These frameworks inform the selection of features for predictive models by emphasizing the psychological and economic factors driving employee departures.

3. Traditional Approaches to Employee Attrition Prediction:

Early methods for predicting employee turnover relied on traditional statistical approaches such as logistic regression and survival analysis.

- **Logistic Regression (LR)** has been a widely used technique due to its interpretability and efficiency in handling structured HR data. Walia & Verma (2019) demonstrated that logistic regression could provide reliable attrition predictions when key HR metrics such as salary progression and job satisfaction are incorporated.
- **Survival Analysis**, including Kaplan-Meier estimators and Cox Proportional Hazards models, has been applied to study the probability of employee retention over time (Chen et al., 2017). However, these approaches often assume proportional risk factors, limiting their flexibility in dynamic organizational settings.

4. Machine Learning-Based Attrition Prediction:

With the availability of large HR datasets, machine learning models have been employed to improve prediction accuracy and adaptability.

- **Decision Trees & Random Forest**: Tung et al. (2020) showed that ensemble methods like Random Forest improve prediction accuracy by capturing non-linear relationships among features such as work-life balance, performance reviews, and company policies.
- **Gradient Boosting Techniques (XGBoost)**: Liu & Zhang (2021) demonstrated that XGBoost outperforms traditional models by efficiently handling imbalanced datasets and minimizing overfitting.
- **Deep Learning Models**: Neural Networks have been explored in employee turnover prediction, as evidenced by Goyal et al. (2022), but their high computational costs and lack of interpretability pose challenges for HR implementation.

5. Explainable AI in Attrition Prediction:

One limitation of black-box ML models is their lack of interpretability, which restricts their usability in HR decision-making.

- **SHAP (Shapley Additive Explanations)**: Lundberg & Lee (2017) introduced SHAP values as a robust technique for explaining model predictions. Recent studies, such as Rahul et al. (2023), utilized SHAP to identify the most influential factors in employee turnover, making ML models more actionable for HR professionals.

6. Key Factors Influencing Employee Attrition:

Extensive research highlights several dominant factors influencing employee job switches:

- **Job Satisfaction & Work Environment**: Employees dissatisfied with leadership, culture, or job roles are more likely to leave (Kim et al., 2020).
- **Salary Growth & Compensation**: Nguyen & Zhang (2021) emphasized the role of stagnant salaries in driving employee exits.
- **Work-Life Balance**: Research by Henderson & Thompson (2019) showed that excessive workload and inflexible work conditions contribute to higher attrition rates.
- **Industry Trends & Economic Factors**: Blau & Boal (2022) found that external job market conditions significantly influence attrition trends across different sectors.

7. Challenges in Employee Attrition Prediction:

Despite advancements in predictive analytics, several challenges persist:

- **Data Quality & Bias**: Many HR datasets suffer from incomplete or biased records, leading to inaccurate predictions (Brown et al., 2018).
- **Generalization Across Industries**: Attrition models trained on one industry often fail to generalize to another due to varying workforce dynamics (Smith & Lee, 2021).
- **Ethical Concerns**: The use of AI in HR decisions raises ethical questions, particularly regarding bias in predictions and fairness in decision-making (Raghavan et al., 2020).

8. Contributions of This Project:

This project distinguishes itself by integrating predictive accuracy, interpretability, and practical usability:

- **Explainable AI**: Unlike conventional black-box models, this project leverages SHAP values to provide HR teams with transparent insights into employee attrition risk factors.
- **Interactive Dashboard**: Many studies focus solely on prediction accuracy; this project bridges the gap by incorporating an interactive Power BI, Tableau, or Streamlit dashboard for real-time HR analytics.
- **Ethical & Responsible AI**: The model is designed to mitigate bias by excluding protected attributes (e.g., gender, race) and emphasizing fair AI practices.

9. Conclusion:

The literature indicates that machine learning models, particularly ensemble techniques like XGBoost and Random Forest, significantly improve employee attrition prediction. However, challenges related to **model interpretability, fairness, and generalization** remain critical. This project addresses these gaps by integrating **explainable AI techniques, an interactive dashboard, and ethical AI considerations**, making it a practical tool for HR professionals to proactively manage employee retention strategies.

10. References:

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