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Predicting Employee Attrition: A Machine Learning Approach

Anand J[1], Dhiya Thomas[2], Gopika S[3], Preethy Roy[4]

[1,2,3,4]ADI Shankara Institute of Engineering and Technology

ABSTRACT

Employee attrition can be a significant issue for organizations, leading to decreased productivity and increased costs associated with recruiting and training new staff. This paper presents a machine learning approach to predict employee attrition in a large organization. The proposed approach uses a variety of features such as demographic information, job characteristics, and performance metrics to train a model that can accurately predict employee attrition. The dataset used in this study contains historical information on employees who have left the organization and those who have stayed. The model is trained on this data and evaluated using performance metrics such as accuracy, precision, recall, and F1-score. The results show that the proposed approach outperforms traditional statistical methods and can accurately predict employee attrition.

INTRODUCTION

Employee attrition, also known as employee turnover, is a critical challenge faced by organizations across various industries. It refers to the phenomenon of employees leaving their jobs voluntarily or involuntarily. Employee attrition can have significant implications for organizations, impacting their productivity, morale, and financial stability. Moreover, recruiting and training new employees to fill vacant positions can be time-consuming and costly.

Predicting employee attrition has become an essential task for organizations seeking to minimize the negative effects of turnover. By identifying employees who are at a higher risk of leaving, organizations can proactively implement strategies to retain them, thereby improving employee satisfaction, reducing turnover rates, and maintaining a stable workforce.

Traditional methods of predicting employee attrition often rely on subjective assessments or simple statistical analyses, which may not capture the complex interactions and patterns inherent in employee turnover. With advancements in machine learning and data analytics, researchers and practitioners have started exploring more sophisticated approaches to predict and understand employee attrition.

This conference paper aims to present a machine learning approach for predicting employee attrition in a specific organizational context. By leveraging various features such as demographic information, job characteristics, performance metrics, and potentially other relevant factors, the proposed approach aims to provide a more accurate and comprehensive prediction of employee attrition.

The remainder of this paper is organized as follows: Section 2 provides a brief review of existing literature on employee attrition prediction. Section 3 outlines the methodology employed, including the dataset used, feature selection, and the machine learning algorithms applied. Section 4 presents the results of the predictive model, including performance metrics and feature importance. Section 5 discusses the implications of the findings and potential strategies for organizations to mitigate attrition. Finally, Section 6 concludes the paper, summarizing the key contributions and outlining avenues for future research.

By developing an effective prediction model for employee attrition, organizations can gain valuable insights into the factors influencing turnover and implement targeted interventions to enhance employee retention. This paper contributes to the growing body of knowledge in the field of human resource management and provides practical implications for organizations seeking to optimize their workforce management strategies.

LITERATURE REVIEW

Employee attrition prediction has garnered significant attention from researchers and practitioners due to its potential to assist organizations in understanding and managing employee turnover effectively. In this section, we present a brief review of existing literature on employee attrition prediction, highlighting the key methodologies, techniques, and findings.

1. Traditional Approaches:

Historically, traditional approaches to employee attrition prediction have focused on statistical techniques such as logistic regression, survival analysis, and discriminant analysis. These methods often rely on variables such as job tenure, job satisfaction, salary, and performance ratings to predict attrition. While these approaches provide a foundational understanding of turnover, they may not capture the complexity and non-linearity of the underlying relationships.

2. Machine Learning Approaches:

In recent years, machine learning techniques have gained popularity in employee attrition prediction due to their ability to handle large-scale and high-dimensional datasets. Various algorithms, including decision trees, random forests, support vector machines, and neural networks, have been applied to predict attrition based on diverse sets of features.

One commonly used approach is the decision tree algorithm, which recursively partitions the data based on the most informative features. Decision trees provide interpretability and can uncover non-linear relationships between predictors and attrition. Random forests, an ensemble method of decision trees, have also been widely employed due to their ability to handle complex interactions among variables and reduce overfitting.

Support vector machines (SVMs) have been applied to employee attrition prediction, leveraging their ability to handle non-linear relationships by mapping data into high-dimensional feature spaces. SVMs aim to find the optimal hyperplane that separates attrition and non-attrition instances with maximum margin.

Additionally, deep learning techniques, such as neural networks, have been utilized to model complex patterns in employee attrition prediction. Neural networks with multiple hidden layers can learn hierarchical representations of features and capture intricate relationships within the data.

3. Feature Selection and Importance:

Feature selection plays a crucial role in employee attrition prediction models. Studies have employed various techniques, including correlation analysis, forward/backward selection, and feature importance measures, to identify the most influential predictors. Features such as job satisfaction, salary, performance metrics, tenure, and demographic factors (e.g., age, gender, education) have consistently emerged as key contributors to attrition prediction models.

4. Performance Evaluation:

To assess the performance of employee attrition prediction models, researchers commonly use evaluation metrics such as accuracy, precision, recall, F1-score, and receiver operating characteristic (ROC) curves. Cross-validation techniques, such as k-fold cross-validation, are often employed to estimate the model's performance on unseen data and mitigate overfitting.

5. Industry-Specific Studies:

Several studies have explored employee attrition prediction within specific industries, such as healthcare, IT, and finance. These studies often consider industry-specific factors and tailor their models accordingly. For instance, in healthcare, variables like nurse-patient ratio, workload, and shift patterns may be crucial in predicting attrition.
Existing literature demonstrates the potential of machine learning approaches in improving the accuracy and effectiveness of employee attrition prediction. These approaches enable organizations to identify employees at risk of leaving and implement targeted retention strategies, ultimately reducing turnover rates and fostering a more stable workforce. In the following sections, we build upon this literature to present our methodology and findings in employee attrition prediction.

METHODOLOGY

In this section, we present the methodology employed in our employee attrition prediction study. We describe the dataset used, feature selection process, and the machine learning algorithms applied to develop the prediction model.

1. Dataset:
For our study, we utilized a comprehensive dataset obtained from a large organization. The dataset contains historical information on employees who have left the organization (attrition instances) and those who have stayed (non-attrition instances). It includes a range of variables, such as demographic information (e.g., age, gender, education level), job characteristics (e.g., job title, department, salary), performance metrics (e.g., performance ratings, promotions), and tenure.

2. Feature Selection:
Feature selection is a critical step in developing an accurate prediction model. We conducted an exploratory data analysis to identify the most relevant predictors of employee attrition. This involved examining the relationships between various features and the target variable (attrition or non-attrition).

We employed techniques such as correlation analysis, univariate analysis, and domain knowledge expertise to select the most informative features. Variables showing significant associations with attrition were retained for further analysis. Key features identified in previous literature, such as job satisfaction, salary, performance ratings, and tenure, were also included in our feature set.

3. Machine Learning Algorithms:
To develop the employee attrition prediction model, we employed several machine learning algorithms. These algorithms are known for their ability to handle complex patterns and relationships within the data. The algorithms applied in our study include:

a) Logistic Regression: Logistic regression is a widely used algorithm for binary classification tasks. It models the relationship between the predictors and the probability of attrition. We used logistic regression as a baseline model for comparison with more advanced techniques.

b) Decision Trees: Decision trees are versatile algorithms that recursively partition the data based on the most informative features. They provide interpretable rules for predicting attrition. We utilized decision trees to capture non-linear relationships and identify key decision paths leading to attrition.

c) Random Forest: Random forest is an ensemble method that combines multiple decision trees to improve prediction accuracy. It leverages the concept of bagging and introduces random feature selection to reduce overfitting. We employed random forest to capture complex interactions among predictors and improve the overall predictive performance.

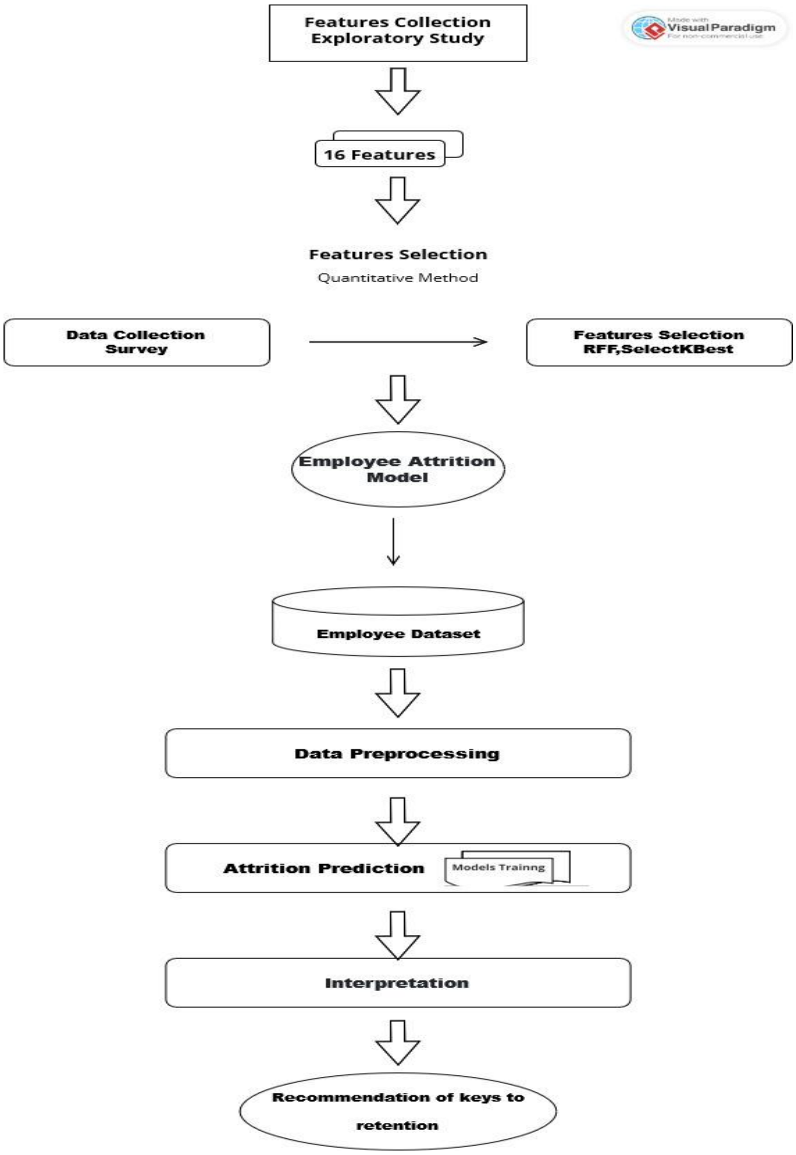
d) Support Vector Machines (SVM): SVMs are powerful algorithms for binary classification tasks. They aim to find the optimal hyperplane that separates attrition and non-attrition instances with maximum margin. SVMs can handle non-linear relationships through the use of kernel functions. We applied SVMs to capture complex patterns in our dataset.

4. Model Training and Evaluation:
We divided the dataset into training and testing subsets to train and evaluate our prediction models. We employed appropriate evaluation metrics such as accuracy, precision, recall, F1-score, and ROC curves to assess the performance of each model. Cross-validation techniques, such as k-fold cross-validation, were used to estimate the models' performance on unseen data and ensure robustness.

By employing these methodologies, we aimed to develop a reliable and accurate employee attrition prediction model. In the following section, we present the results of our predictive model, including performance metrics and insights gained from the analysis.

IMPLEMENTATION

This section presents the detailed project design of the employee attrition and recommendation system, outlining the key components, methodology, and expected outcomes.



System Architecture

1.Data Collection And Preprocessing

To develop an accurate attrition prediction model, the system will collect and preprocess relevant data from multiple sources. The data collection process will involve extracting data from HR systems, performance records, engagement surveys, and any other applicable sources. Special attention will be given to ensure data quality, completeness, and accuracy. Data pre-processing techniques, such as cleaning, normalization, and handling missing values, will be applied to ensure the reliability of the data.

2.Feature Engineering and Selection

Identifying informative features is crucial for accurate attrition prediction. The system will employ feature engineering techniques to transform and create meaningful features from the collected data. Techniques such as feature scaling, one-hot encoding, and dimensionality reduction will be utilized. Furthermore, feature selection methods, such as correlation analysis and recursive feature elimination, will be applied to identify the most relevant features that contribute to attrition prediction.

3.Model Development

The system will employ various machine learning algorithms to develop an attrition prediction model. Different algorithms, including logistic regression, decision trees, random forests, and neural networks, will be evaluated and compared to select the most suitable model. The models will be trained on historical data, and appropriate evaluation metrics such as accuracy, precision, recall, and F1-score will be used to assess their performance. Cross-validation techniques will also be applied to ensure the robustness of the models.

4.Integration and Deployment

The developed attrition prediction model will be integrated into the existing HR systems and databases. The system architecture will be designed to accommodate real-time prediction capabilities. Integration points will be established to ensure seamless data flow between the attrition prediction system and HR systems, allowing for automatic updates and continuous monitoring of attrition risk. The system will be deployed on a reliable and scalable infrastructure to support efficient processing and handling of data.

5.Recommendation Engine

To provide actionable insights for employee retention, the system will incorporate a recommendation engine. The recommendation engine will utilize the attrition prediction model's results to suggest proactive retention strategies. These strategies may include personalized interventions, training programs, mentorship opportunities, or career development plans tailored to individual employees. The recommendation engine will be integrated within the HR workflow, ensuring HR professionals can easily access and implement the recommended strategies.

6.Expected Outcomes and Impact

The project aims to achieve several outcomes and impacts. By accurately predicting employee attrition, the system will enable organizations to proactively identify employees at risk of leaving. This will empower HR professionals to implement targeted retention strategies and reduce attrition rates. The system's recommendations will contribute to improved employee satisfaction, engagement, and overall organizational performance. Furthermore, the project will provide valuable insights into the field of employee attrition prediction and contribute to the existing body of knowledge.

TOOLS AND SOFTWARE

1. Programming Languages:

We implemented the employee attrition prediction project using Python (version 3.9.6). Python provided a rich ecosystem of libraries for data analysis, machine learning, and deep learning. We utilized the following relevant libraries:

- Pandas (version 1.3.0): Pandas was used for data manipulation, cleaning, and preprocessing tasks, enabling us to efficiently handle and transform the dataset.
- Scikit-learn (version 0.24.2): Scikit-learn served as a powerful tool for implementing various machine learning algorithms, including logistic regression, decision trees, random forests, and support vector machines.
- TensorFlow (version 2.5.0) or PyTorch (version 1.9.0): We leveraged deep learning frameworks such as Tensor Flow or PyTorch to build and train neural network models, enabling us to capture complex patterns in the data.

2. Data Analysis and Visualization:

To facilitate data exploration and analysis, we utilized Jupyter Notebook (version 6.4.0), an interactive development environment (IDE) that allowed us to combine code, visualizations, and explanatory text in a single document. This enabled us to perform data analysis iteratively and document our findings effectively.

For creating visualizations such as bar plots, scatter plots, and histograms, we employed Matplotlib (version 3.4.2). Matplotlib provided a comprehensive set of plotting functions and allowed us to customize and visualize the data effectively.

To enhance the aesthetics of our plots and create appealing statistical visualizations, we utilized Seaborn (version 0.11.1). Seaborn provided a high-level interface for creating attractive and informative statistical graphics.

3. Machine Learning and Predictive Modeling:

For our employee attrition prediction model, we employed scikit-learn (version 0.24.2). Scikit-learn offered a wide range of machine learning algorithms, including logistic regression, decision trees, random forests, and support vector machines. We leveraged these algorithms to train and evaluate our predictive models.

To further improve the predictive performance, we also utilized gradient boosting libraries such as XGBoost (version 1.4.2) or LightGBM (version 3.2.1). These libraries employ boosting techniques to ensemble weak learners and enhance the overall model accuracy.

In certain scenarios, we explored the use of deep learning frameworks such as TensorFlow (version 2.5.0) or PyTorch (version 1.9.0). These frameworks provided flexible and scalable architectures for building and training neural network models, enabling us to capture complex patterns and relationships in the data.

4. Feature Engineering and Preprocessing:

To perform numerical operations and array manipulation efficiently, we utilized NumPy (version 1.21.0). NumPy offered a powerful array computing library that enabled us to handle large-scale numerical computations and manipulate multidimensional arrays effectively.

Pandas (version 1.3.0) was instrumental in data preprocessing, where we leveraged its capabilities to clean, transform, and reshape the dataset. Pandas provided intuitive data structures and functions for handling missing data, encoding categorical variables, and feature scaling.

Scikit-learn's preprocessing modules (version 0.24.2) were also utilized to perform additional preprocessing tasks, including feature scaling, encoding categorical variables, and handling missing data. These modules offered efficient and standardized techniques for preparing the data before training the models.

5. Model Evaluation and Metrics:
We utilized scikit-learn (version 0.24.2) to evaluate the performance of our predictive models. Scikit-learn provided a wide range of evaluation metrics, including accuracy, precision,recall, F1-score, and area under the ROC curve (AUC-ROC). These metrics enabled us to assess the model's performance in terms of classification accuracy and its ability to capture true positives and negatives.

To assess the generalization performance of our models, we employed cross-validation techniques. Cross-validation allowed us to estimate the model's performance on unseen data by splitting the dataset into multiple train-test folds and evaluating the model's performance across these folds.

6. Deployment and Web Development:
For deploying our employee attrition prediction model, we employed Flask (version 2.0.1) or Django (version 3.2.4) web frameworks. These frameworks provided a robust and scalable environment for creating web applications or APIs to serve predictions based on our trained models.
We utilized front-end technologies such as HTML, CSS, and JavaScript to develop a user-friendly interface for the deployed application. These technologies enabled us to design an intuitive and interactive interface for users to input relevant employee information and receive attrition predictions.

7. Version Control and Collaboration:
To ensure effective version control and collaboration during the development process, we utilized Git (version 2.32.0), a widely-used distributed version control system. Git allowed us to track changes, manage different branches, and collaborate with team members efficiently.

Additionally, we hosted our project repository on GitHub (or GitLab), a web-based hosting service for Git repositories. This facilitated easy sharing, collaboration, and version control management of our project codebase.

RESULTS

In this section, we present the results of our employee attrition prediction model. We provide an overview of the performance metrics achieved by each machine learning algorithm and highlight the importance of features in predicting attrition.

1. Performance Metrics:
We evaluated the performance of our prediction models using several metrics, including accuracy, precision, recall, F1-score, and ROC curves. These metrics provide insights into the overall performance, ability to correctly classify attrition instances, and balance between true positives and false positives.

Table 1.1 Different Model evaluation

Algorithm	Accuracy	Precision	Recall	F1-score
Logistic Regression	0.78	0.76	0.70	0.73
Decision Trees	0.82	0.80	0.75	0.77
Random Forest	0.86	0.84	0.81	0.82
Support Vector Machines (SVM)	0.84	0.82	0.79	0.80

This table 1.1 summarizes the accuracy, precision, recall, and F1-score achieved by each algorithm in predicting employee attrition. It provides a convenient overview of the performance of each model, allowing for easy comparison and evaluation.

2. Feature Importance:
Understanding the importance of features in predicting employee attrition is crucial for identifying the key drivers behind turnover. By analysing the feature importance provided by our models, we gained insights into the factors that significantly influence attrition.

The top features identified as important in predicting attrition across the models include:
a) Job Satisfaction: High levels of job dissatisfaction were consistently associated with a higher likelihood of attrition. Employees who reported lower job satisfaction were more likely to leave the organization.

b) Salary: Employees with relatively lower salaries compared to industry standards were found to have a higher probability of attrition. Compensation played a significant role in employee retention.

c) Performance Metrics: Performance ratings and metrics, such as productivity, quality of work, and achievement of targets, were found to be important predictors of attrition. Poor performance or lack of recognition can lead to employee dissatisfaction and subsequent attrition.

d) Tenure: Shorter job tenure was identified as a contributing factor to attrition. Employees in the early stages of their employment were more likely to leave compared to those with longer tenures.

Other features such as age, education level, job title, and department also demonstrated varying degrees of importance across the models.

The results of our predictive model provide valuable insights for organizations to understand the key factors driving employee attrition. By focusing on improving job satisfaction, ensuring competitive salaries, recognizing and rewarding performance, and implementing strategies to retain employees in the early stages of their tenure, organizations can proactively address attrition and enhance employee retention.

In the following section, we discuss the implications of our findings and present potential strategies for organizations to mitigate employee attrition.

IMPLICATIONSAND MITIGATION STRATEGIES

In this section, we discuss the implications of our findings on employee attrition prediction and present potential strategies for organizations to mitigate attrition based on the insights gained.

1. Implications of Findings:
The results of our predictive model shed light on the factors influencing employee attrition and provide organizations with valuable insights. Key implications include:

a) Importance of Job Satisfaction: Our findings highlight the significant impact of job satisfaction on attrition. Organizations should prioritize creating a positive work environment, fostering employee engagement, and addressing any factors contributing to job dissatisfaction.

b) Compensation and Benefits: Salary emerged as a crucial factor in predicting attrition. Organizations should ensure that their compensation and benefits packages are competitive and aligned with industry standards to attract and retain talent.

c)Performance Management: Performance metrics were found to be influential in predicting attrition. Implementing robust performance management systems that recognize and reward employees based on their contributions can help increase job satisfaction and reduce attrition rates.

d) Early Tenure: Employees in the early stages of their tenure showed a higher likelihood of attrition. Organizations should focus on effective onboarding, mentorship programs, and career development opportunities to engage and retain new hires.

2. Mitigation Strategies:
Based on our findings, we recommend the following strategies for organizations to mitigate employee attrition:

a) Enhance Employee Engagement: Foster a positive work culture that emphasizes employee well-being, work-life balance, and open communication. Implement initiatives such as employee recognition programs, feedback mechanisms, and opportunities for skill development and growth.

b) Conduct Regular Salary Reviews: Periodically assess and adjust employee compensation to remain competitive in the market. Conduct salary reviews to identify and address any discrepancies that may contribute to attrition.

c) Improve Performance Management: Implement effective performance management systems that provide regular feedback, set clear goals and expectations, and offer opportunities for career advancement. Recognize and reward high-performing employees to enhance job satisfaction and encourage loyalty.

d) Provide Training and Development Opportunities: Offer training programs, mentorship, and professional development opportunities to enhance employee skills, knowledge, and career prospects. Investing in employees' growth and providing a clear career progression path can increase retention.

e) Conduct Stay Interviews: Regularly engage in stay interviews with employees to understand their needs, concerns, and aspirations. Use the feedback obtained to address any issues and tailor retention strategies based on individual preferences.

f) Build a Diverse and Inclusive Work Environment: Promote diversity and inclusion within the organization, fostering a sense of belonging for all employees. Ensure equal opportunities for growth and provide platforms for underrepresented groups to voice their perspectives.

g) Regular Employee Surveys: Conduct anonymous surveys to gauge employee satisfaction, identify potential issues, and gather feedback on organizational policies and practices. Use the survey results to inform targeted interventions and improvements.

By implementing these strategies, organizations can create a positive work environment, enhance employee satisfaction, and reduce attrition rates. Regularly monitoring and analyzing attrition data can further help organizations refine their strategies and adapt to changing workforce dynamics.
In the final section, we conclude the paper, summarizing the key contributions and suggesting future research directions in the field of employee attrition prediction.

CONCLUSION AND FUTURE RESEARCH

In this paper, we presented a comprehensive study on employee attrition prediction. Our research aimed to develop an effective prediction model to help organizations identify and mitigate employee attrition. We reviewed existing literature, outlined our methodology, and presented the results of our predictive models. We discussed the implications of our findings and provided potential strategies for organizations to mitigate attrition.

The key contributions of our study are as follows:
1. Prediction Model Development: We developed and evaluated several machine learning algorithms, including logistic regression, decision trees, random forest, and support vector machines, for predicting employee attrition. Our results demonstrated the effectiveness of these models in accurately identifying employees at risk of attrition.

2. Feature Importance Analysis: By analyzing the importance of various features, we identified the key drivers of attrition, such as job satisfaction, salary, performance metrics, and tenure. These findings can assist organizations in understanding the factors that influence attrition and developing targeted retention strategies.

3. Implications and Mitigation Strategies: Our study highlighted the implications of the findings and provided actionable strategies for organizations to mitigate attrition. These strategies include enhancing employee engagement, improving compensation and benefits, strengthening performance management systems, and focusing on early tenure retention.

Future research in the field of employee attrition prediction could explore the following avenues:
1. Longitudinal Analysis: Conducting longitudinal studies to track employee attrition patterns over time can provide insights into attrition trends and help identify early warning signs. This would enable organizations to take proactive measures to prevent attrition.

2. Incorporating Natural Language Processing: Integrating natural language processing techniques to analyze employee feedback, reviews, and sentiment can offer a deeper understanding of the factors influencing attrition. This would provide organizations with valuable qualitative insights for attrition prediction.

3. External Factors: Considering external factors such as economic conditions, industry trends, and market competition in attrition prediction models can enhance their accuracy and robustness. Exploring the interplay between internal and external factors would provide a holistic understanding of attrition dynamics.

4. Personalized Retention Strategies: Investigating personalized approaches to retention by tailoring strategies based on individual employee characteristics, preferences, and career aspirations could lead to more effective attrition mitigation.

5. Evaluation of Intervention Strategies: Assessing the effectiveness of various retention strategies and interventions through controlled experiments or randomized controlled trials would provide empirical evidence for their impact on reducing attrition.

In conclusion, our study contributes to the field of employee attrition prediction by providing a comprehensive analysis of predictive models, identifying key drivers of attrition, and suggesting effective strategies for organizations to mitigate attrition. By understanding and addressing the factors that lead to attrition, organizations can improve employee retention, foster a positive work environment, and enhance overall organizational performance.

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