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Gender-Based Analysis of Employee Attrition Prediction Using Machine Learning

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Employee turnover is a significant problem in organizations because it comes with productivity and cost implications. This paper focuses on predicting employee turnover using machine learning techniques that incorporate gender aspects. We used strong Random Forest classifiers to predict attrition based on a wide cross-section of the employee's activities and the feature importance assessment. The procedure involved data cleaning, splitting the dataset for males and females, creating models for them, and using assessment tests with different measures. When we separated the database by gender, our analysis identified unique factors that predisposed the two groups to drop out. The importance of features, the ROC curve, and the SHAP map showed how variables such as "job role," "monthly income," and "work-life balance" affected attrition differently between males and females. For female employees, job satisfaction and time directly influenced attrition, whereas for male employees, previous companies and distance from home had a greater impact. The results of the research therefore imply the need for gender-sensitive HR practices that can inform the development of gender-sensitive accommodation policies as a way of responding to the challenges facing each gender. This approach aids in the explanation of attrition tendencies and the provision of better organizational practices.

Keywords: Employee Attrition; Machine Learning; Gender Analysis; Random Forest; SHAP Values

Introduction:

Job satisfaction is a critical determinant of employee turnover, as it has a direct impact on organizational costs in terms of recruitment, training, and losing experienced employees [1] [2]. It is critical to understand the reasons for voluntary turnover before adopting strategic solutions that will increase retention rates. However, gender differences in employee attrition have received limited attention. Analyzing gender differences to each type of turnover is crucial when analyzing the consequences of turnover predictors, which vary for male and female employees. Therefore, organizations can use this information to guide their decision-making process when implementing specific retention strategies. For example, satisfaction with working conditions, overtime, availability for work, customs, etc. may affect male and female personnel differently. Understanding the causes of these differences makes it easier to find a cure, thereby reducing turnover costs.

Other studies have identified antecedents such as job satisfaction, organizational commitment, work-life interface, pay, career mobility, and job content. However, the extension of statistical and machine learning methods to investigate the gender-specific effects is quite limited. Shortly, due to modern development in machine learning, especially with the use of Random Forests, it becomes possible to handle an increased number of variables within their interactions to provide a better understanding of the turnover factors. SHAP provides extra information on feature attributions [3]. However, gender differentiation in the turnover literature is still limited. This paper starts with data pre-processing, which entails the general management of the categorical data and the records with missing values. Subsequently, we develop gender-specific two-class Random Forest classifiers to assess employee attrition [4] [5]. We measure the model's accuracy and effectiveness in terms of precision, recalls, and the area under the curve of the receiver operating characteristic (AUC-ROC). Next, the extracted SHAP values allow for the construction of explanations of critical attrition features for each gender. We conduct a final comparison on these gender-specific predictors to provide insights into the differences in turnover factors between male and female employees. Thus, the holistic observation of gender-specific dropout rates guarantees a much more precise approach to the determination of relevant retention measures.

This research aims to develop and assess machine learning algorithms that are specifically tailored to analyze attrition based on gender. Therefore, we recommend using more advanced techniques to identify the underlying factors that contribute to gender-specific turnover. This approach can facilitate the development of targeted measures to enhance employee retention rates. The findings in this study have the potential to greatly advance the development of innovative strategies for employee retention, which might effectively address the persistent deficiencies in workplace policy.

Literature Review:

Employee turnover has negative effects on organizational performance and financial returns. The most recent literature identifies several factors that impact attrition, emphasizing the importance of understanding these factors to introduce effective retention strategies. Job satisfaction is a significant predictor of turnover. According to Herzberg's Two-Factor Theory, inadequate pay and poor working conditions lead to dissatisfaction; by contrast, accomplishment and recognition lead to satisfaction. In support of this theory, Spector [6] conducted a study that revealed a high correlation between job satisfaction and turnover intentions. Another current issue worth mentioning is work-life balance. Workers who cannot effectively manage their work-family interface are likely to quit their jobs. Allen et al. emphasized that issues related to the work-family interface can negatively impact stress levels and job satisfaction, which in turn can lead to increased turnover intentions [7]. Compensation can also be considered as another factor that influences the extent of gender equality. Twalib and Magutu assert that job seekers seek employment due to their dissatisfaction with work and compensation. To retain employees, various organizations must pay their employees fairly as compared to other organizations [8].

Having opportunities for promotion is crucial for maintaining employee stability. Phyu et al. reached a similar conclusion, arguing that high turnover rates stem from a lack of career paths and training [9]. Mobile employees feel that they are not making any progress in the company, and as a result, they will consider leaving the company.

Random forest and Support Vector machines, among others, are some of the machine learning approaches and several methods applied in analyzing turnover. In particular, according to Fallucchi et al.'s work, it is clear that these techniques guarantee higher accuracy and more suitable interpretation of turnover indicators [10]. Random Forests, a decision tree technique that utilizes multiple decision trees to handle a variety of interactions and data, proves to be an ideal tool for attrition prediction. Pratt et al. have described random forests as an apt method for dealing with the various relations within complex data [11].

While there are indications of gendered approaches in the analysis of turnover, there is comparatively less literature that focuses on gender differences. Therefore, Al-Suraihi et al.'s recommendations predict that male and female employees will experience and expect different turnover patterns [12]. SHAP values provide a fresh perspective to assessing the relative importance of features in making the model prediction. Lundberg and Lee also elucidate that SHAP values enhance the explanation of concrete patterns underlying the turnover by offering better directions [3]. Combining gender perspective with machine learning-based methods opens up new possibilities in employee turnover analysis. The study by Jamsandekar and Naik also suggests that identifying the causes of attrition can enhance retention strategies [13].

Material and Methods:

This study investigates employee attrition using Kaggle's "IBM HR Analytics Employee Attrition & Performance" dataset. The dataset includes 1,450 records reflecting employee characteristics and turnover behavior. Although not geographically specific, it provides a robust basis for analyzing employee retention from various perspectives, such as job positions, working distance from home, education level, and monthly income.

Sources:

The data source for the primary data collection is Kaggle's "IBM HR Analytics Employee Attrition & Performance" set. IBM data specialists established the current dataset, which includes hierarchical data about job titles, education levels, distance to home, and other attributes, making it ideal for this research.

Table 1. Sample Data from the IBM HR Analytics Employee Attrition

Age	Attrition	Daily Rate	Department	Distance From Home	Environment Satisfaction	Gender	Job Involvement	Job Satisfaction	Over 18
41	Yes	1102	Sales	1	2	F	3	4	Y
49	No	279	R&D	8	3	M	2	2	Y
37	Yes	1373	R&D	2	4	M	2	3	Y
33	No	1392	R&D	3	4	F	3	3	Y

Data Preprocessing:

Predictor variables always include categorical variables, which need to be transformed into machine-learning input formats. We refer to this transformation as one-hot encoding, which transforms categorical data into a series of binary columns. We also used a technique of standardizing the features to prevent non-convergence issues in the model, as the variables now fall within a narrow range and exhibit less variability than before. As shown in Figure 1, we applied the Synthetic Minority Oversampling Technique (SMOTE) to address the class imbalance problem, a characteristic of attrition datasets. Specifically, SMOTE synthesizes new samples to address the problem of giving minimal attention to the minority class, commonly known as attrition classes, and bring more samples to the required proportions in the dataset.

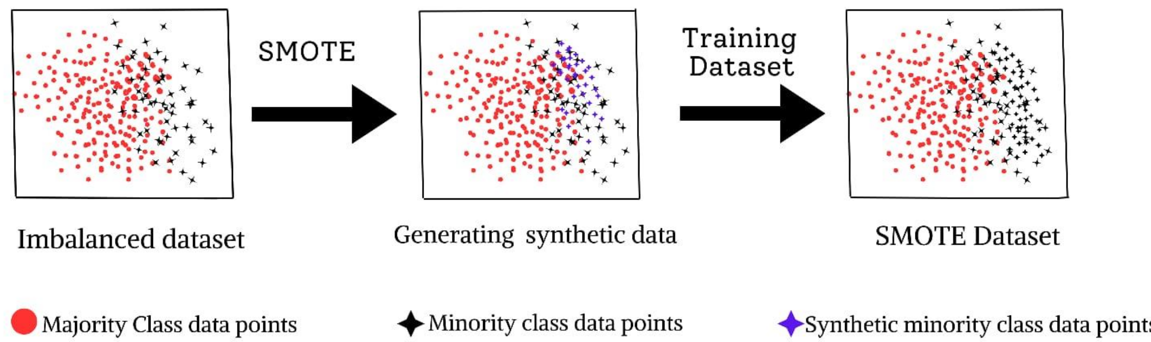

Figure 1. Balancing Attrition Classes Using SMOTE Architecture

Feature Engineering:

Feature engineering involved operations such as converting data into a form that machine learning models could take. We one-hot encoded the categorical variables, such as job roles and educational levels, and normalized the numeric variable, monthly income. These transformations enhanced the model's data learning attribute, leading to more effective analysis.

Model Training:

We only used Random Forest classifiers due to their usefulness for large datasets and their ability to rank the features. Here, we used GridSearchCV to adjust the hyperparameters, which helped us arrive at the optimal model settings, as illustrated in Figure 2. This approach was effective in improving the most optimal Random Forest models for assessing employee attrition rates.

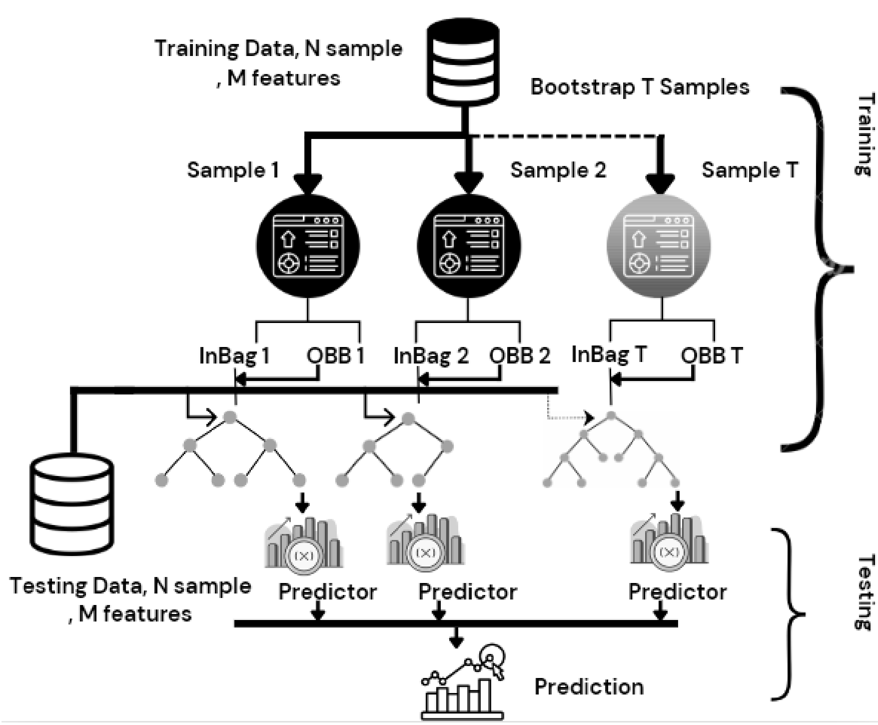

Figure 2. Hyperparameter Tuning for Random Forest Classifier Using GridSearchCV.

Gender-Based Analysis:

We carried out the analysis using gender-based categories to identify attrition rates among male and female employees, we used gender-based categories. This segmentation enabled the determination of factors that might be unique to male or female students, thus affecting their attrition rate. To analyze gender differences in attrition, we constructed two additional random forest models for male and female datasets, respectively.

Evaluation Metrics:

The performance indicators used for the assessment of the model were: accuracy, precision, recall, F1-score, and AUC. The confusion matrix provided a summary of the model's efficiency: TP represented actual positives correctly classified, FP represented actual negatives incorrectly classified as positives, FN represented actual positives misinterpreted as negatives, and TN represented the number of actual negatives correctly classified. Based on their performance on AUC scores and ROC curves, we validated the capability of the models in the classification of the attrition and non-attrition classes.

Visualization Techniques:

We used several visualizations to show the results. We presented the results using a variety of visuals. We defined decision variables and presented bar graphs to determine the company's key priorities that affect the employee turnover rate. Therefore, we utilized methods like confusion matrices to assess the outcomes of the models under study and estimated their relative efficiency using ROC curves. To interpret the model's performance for the post-evaluation, SHAP (Shapley Additive exPlanations) was employed to understand which feature contributed to the prediction of the attrition issue demonstrated in Figure 3.

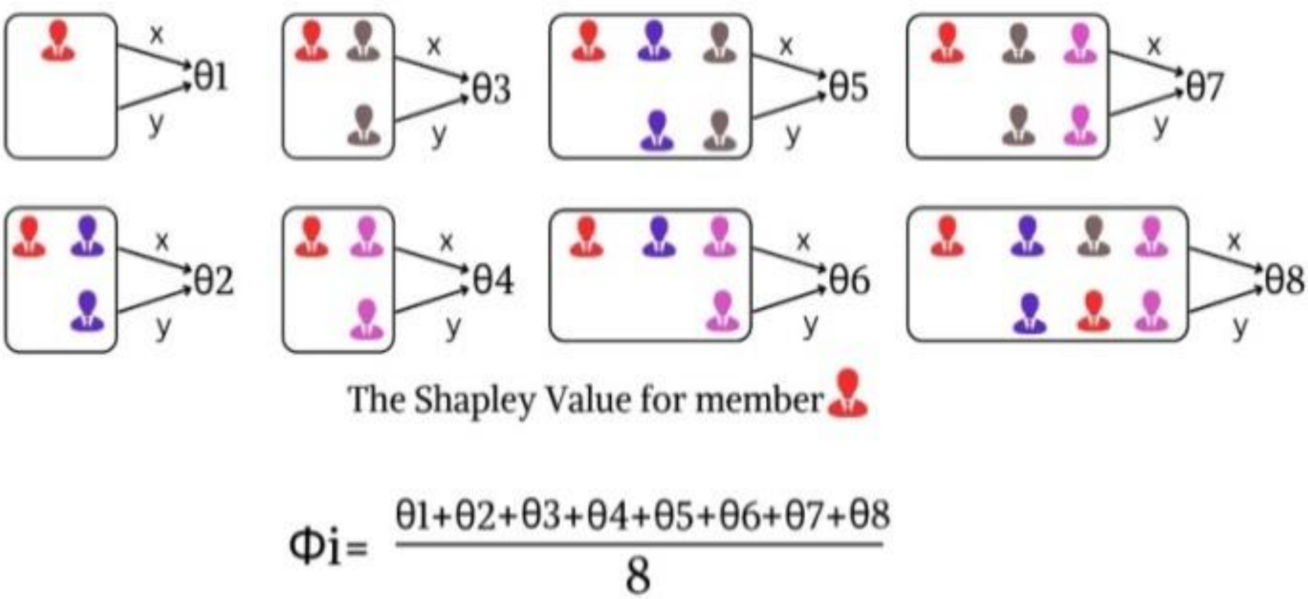

Figure 3. Model Evaluation and Feature Importance Analysis using SHAP architecture.

Additional Validation Methods:

In addition to cross-validation, several other validation techniques bolster confidence in the generalization of the obtained models. We can implement the holdout validation strategy, dividing the data into a testing set and conducting the actual testing on this set. The stratified sampling technique played a crucial role in maintaining the random distribution of classes in both the training and testing samples compared to the general population. We can also perform a variance examination to analyze the model's sensitivity to changes in various parameters in its calibration and improve the credibility and robustness of the model outcomes. This validation approach ensured that the models performed well not only in the provided dataset but also in various other datasets.

Real-Time Applicability:

In this research, we propose the methods to be applicable and practical in organization settings and other relevant settings. The activities involved include data pre-processing, model identification, model assessment, and model validation procedures that are simple and straightforward so that others can execute them with less or without direction. This guarantees that the findings and methods used in the study are useful and simple to comprehend by the acting workforce and other researchers in human resource and employee management. Flow of Methodology is shown in Figure 4 below:

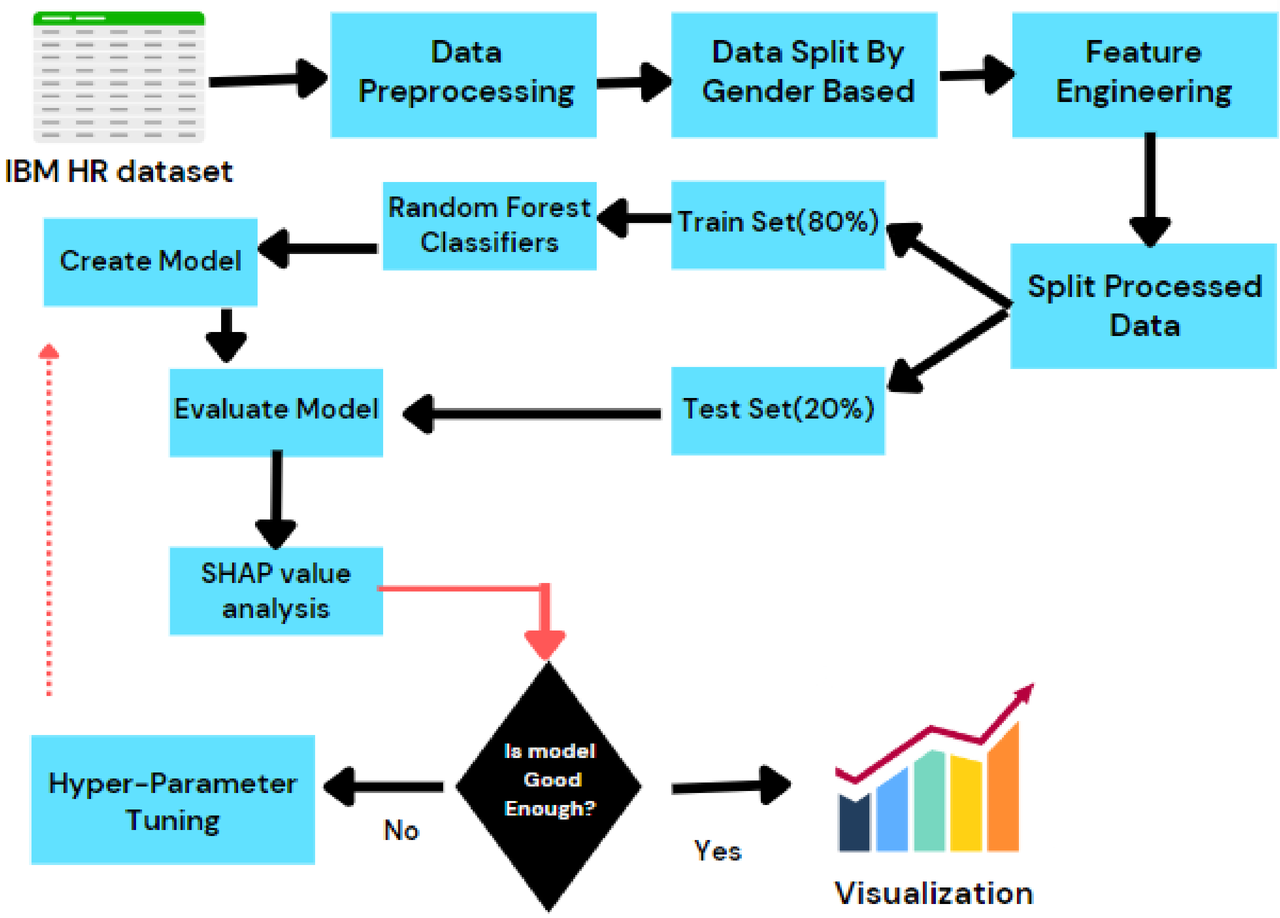

Figure 4. Comprehensive Flow of Methodology using Random Forest and Grid Search

Results and Discussion:

Model performance overview:

We employed Random Forest Classifiers to analyze the attrition rates among employees, segmenting the data based on gender. The model's performance evaluation primarily focused on accuracy, precision, recall, and the F1-score. Models propose near-perfect accuracy rates, excluding the decision tree model, scoring about 0.93 for female employees and 0.88 for all the male employees in the company.

Performance Metrics Analysis:

Table 2 shows the performance metrics of female employees, while Table 3 represents the same for male employees. The Random Forest Classifier yielded an accuracy score of 0.93 for female employees and 0.88 for male employees. Higher values in the precision, recall, and F1-score measures again support the fact that the employed models can correctly identify the causes of attrition. To support these findings, it is critical to acknowledge the efficiency of the models in terms of correctly identifying the primary factors behind employee turnover.

Table 2. Performance Metrics for Female Employees Using Random Forest Classifier

	Precision	Recall	F1 Score	Support
Class 0	0.89	0.98	0.93	151
Class 1	0.98	0.88	0.92	150
Accuracy			0.93	301
Macro Avg	0.93	0.93	0.93	301
Weighted Avg	0.93	0.93	0.93	301

Table 3. Performance Metrics for Male Employees Using Random Forest Classifier

	Precision	Recall	F1 Score	Support
Class 0	0.88	0.88	0.88	214
Class 1	0.88	0.88	0.88	226
Accuracy			0.88	440
Macro Avg	0.88	0.88	0.88	440
Weighted Avg	0.88	0.88	0.88	440

Confusion matrix insights:

Figure 5 displays the confusion matrix for female datasets, while Figure 6 displays the confusion matrix for male datasets. This situation implies that the models are of similar reliability when it comes to predicting the cases of attrition and non-attrition. The matrices aid in the determination of the error distribution and are useful, particularly for further model improvement.

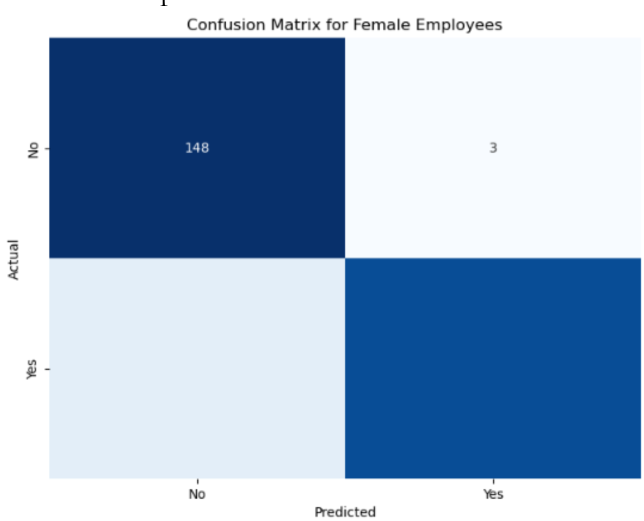

Figure 5. Confusion Matrix for Female Employee Data

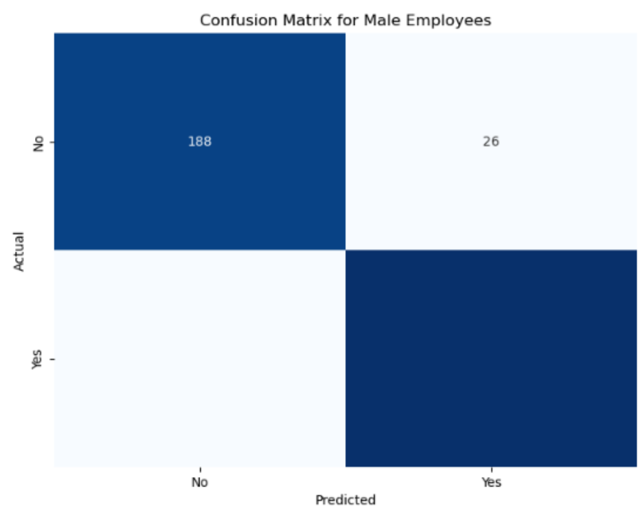

Figure 6. Confusion Matrix for Male Employee Data

ROC curve analysis:

The thresholds for the predictors, overviewed in the ROC curves in Figures 7 and 8, depict the true positive rate that corresponds to the false positive rate. Both curves are located near the upper left corner, demonstrating the model's high ability to distinguish between attrition and non-attrition groups. The female model's AUC score is nearly 0.90, while the male model's is 0.96 percent, which, as known, is an indicator of the model's efficient classification of attrition.

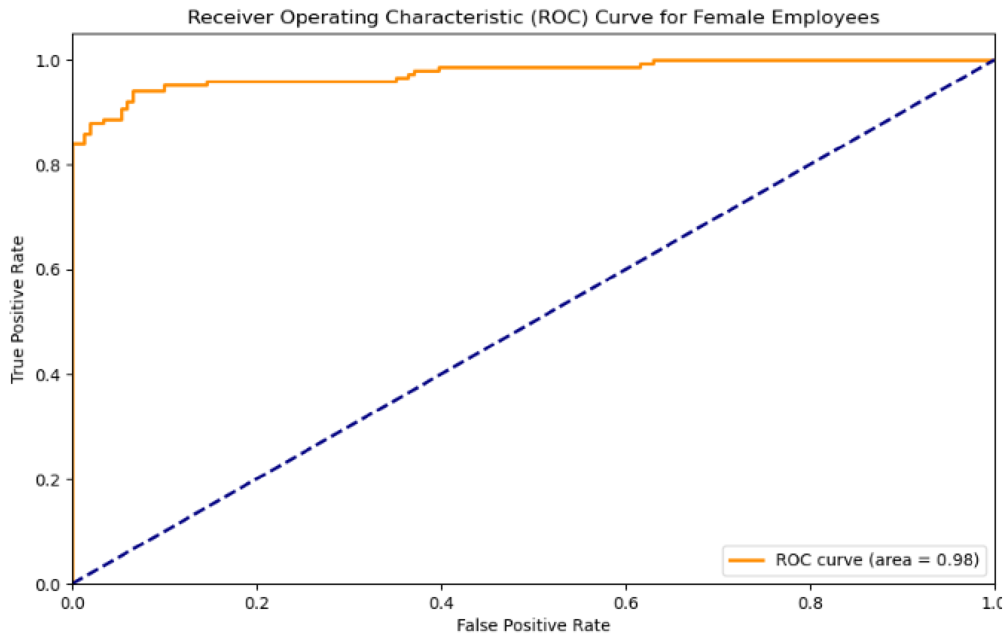

Figure 7. ROC Curve for Female Employee Data

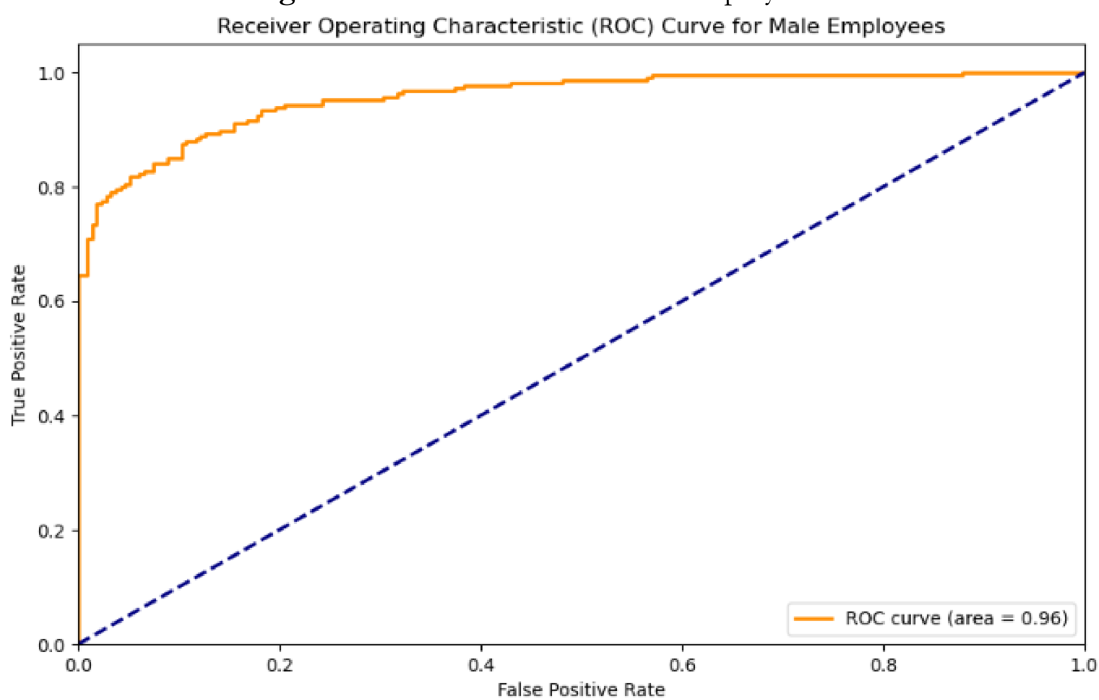

Figure 8. ROC Curve for Male Employee Data

Precision-recall curve insights:

Figures 9 and 10 present the precision-recall curves of both datasets. These curves emphasize the probability of classifying the instances correctly against the probability of identifying the majority and the misclassification or attrition class. Their plots give a more comprehensive picture of the models' performance than the ROC curves do. From PR curves, it is evident that the performance of the different models in terms of precision and recall is almost similar, and the difference, if any, is minimal. This implies that both discussed models are equally efficient in predicting attrition levels, with minimal false positives and false negatives.

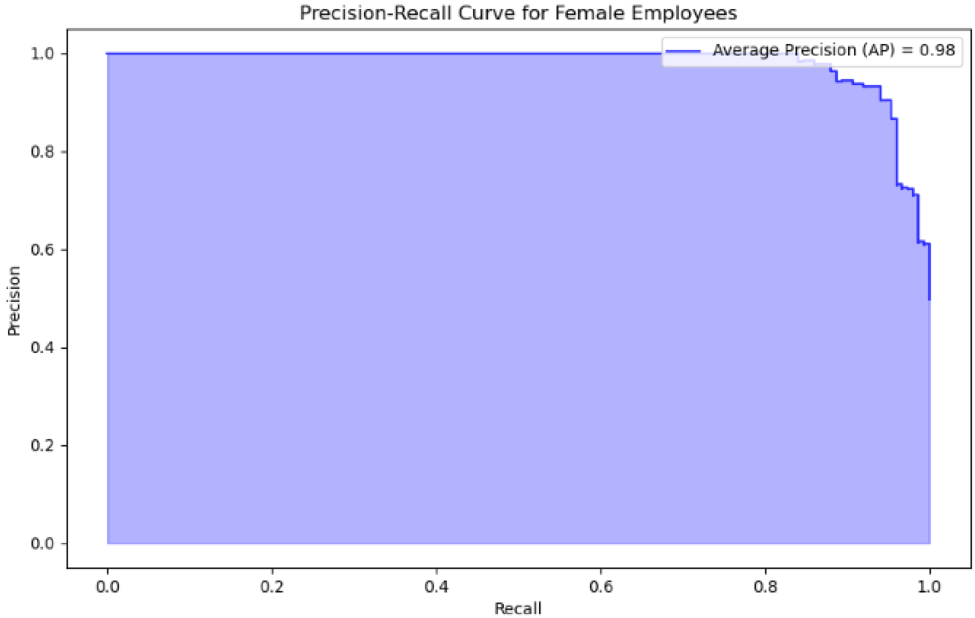

Figure 9. Precision-Recall Curve for Female Employee Data

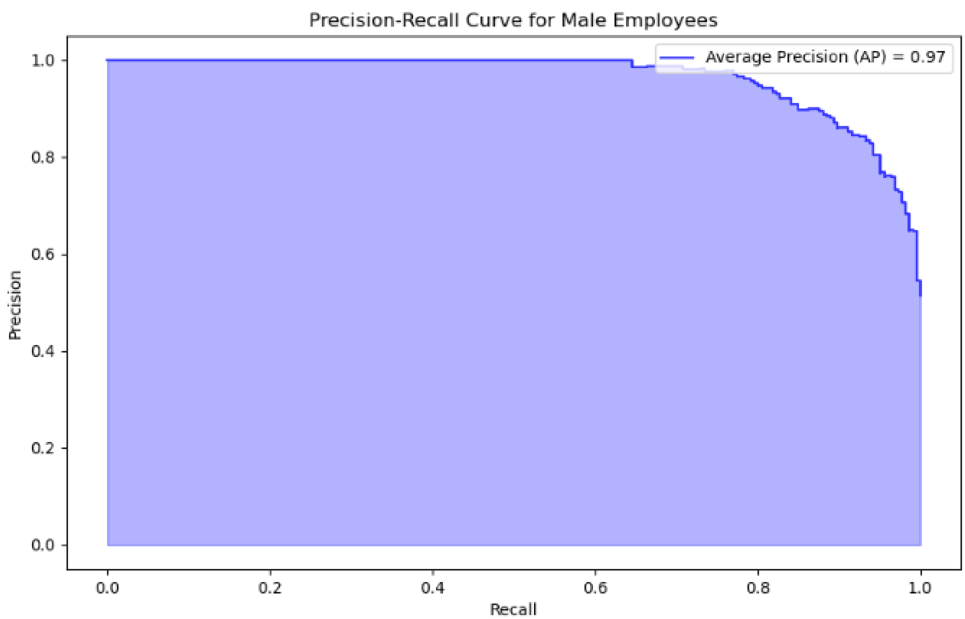

Figure 10 Precision-Recall Curve for Male Employee Data

Feature Importance Analysis:

We assessed feature importance to identify the factors most influential in employee turnover. Figures 11 and 12 illustrate the top features of the female and male datasets, respectively. Key features identified include monthly income, distance from home, and job position within the organization. These factors are significant and align with established findings in employee retention studies. The analysis revealed that monthly income and proximity to the employee's home are the most impactful factors, consistent with previous research on employee satisfaction and turnover.

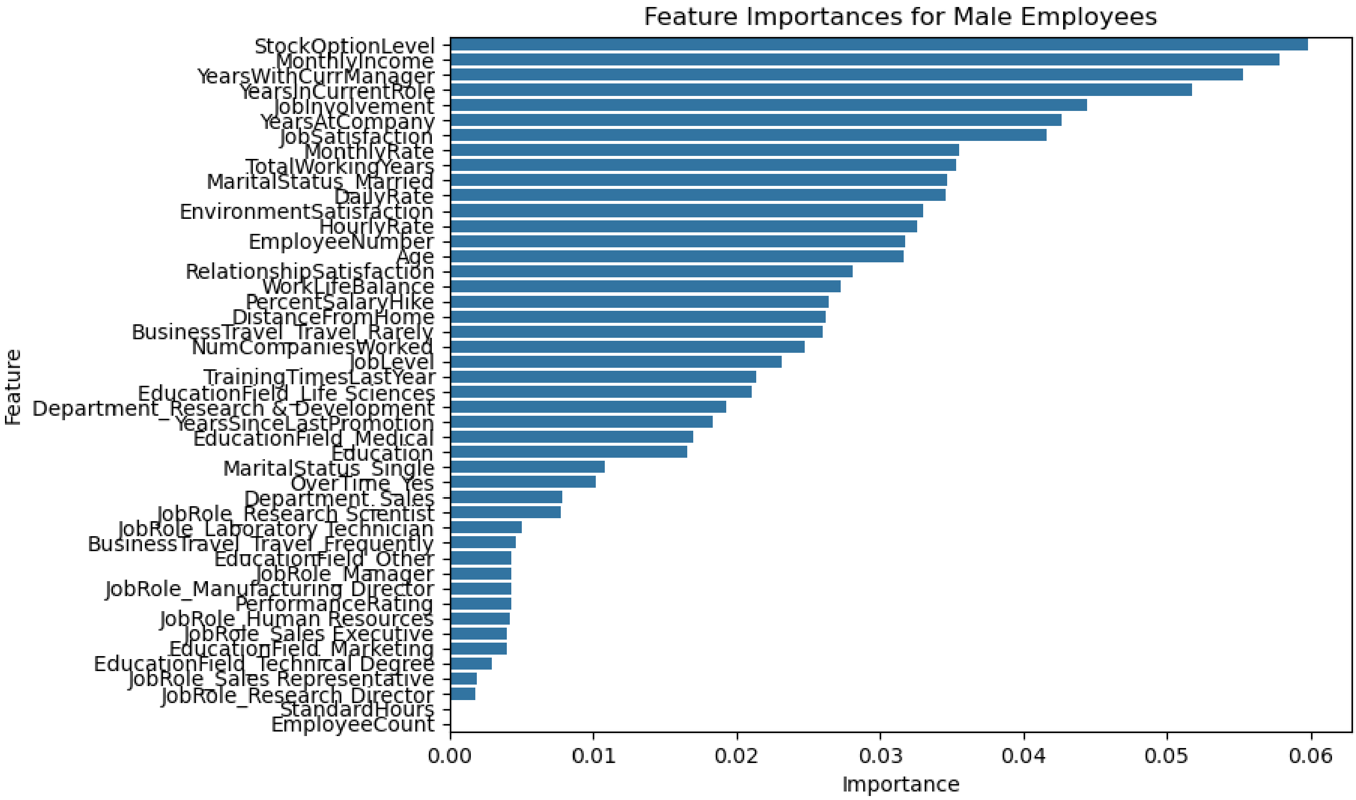

Figure 11. Feature Importance for Female Employee Data

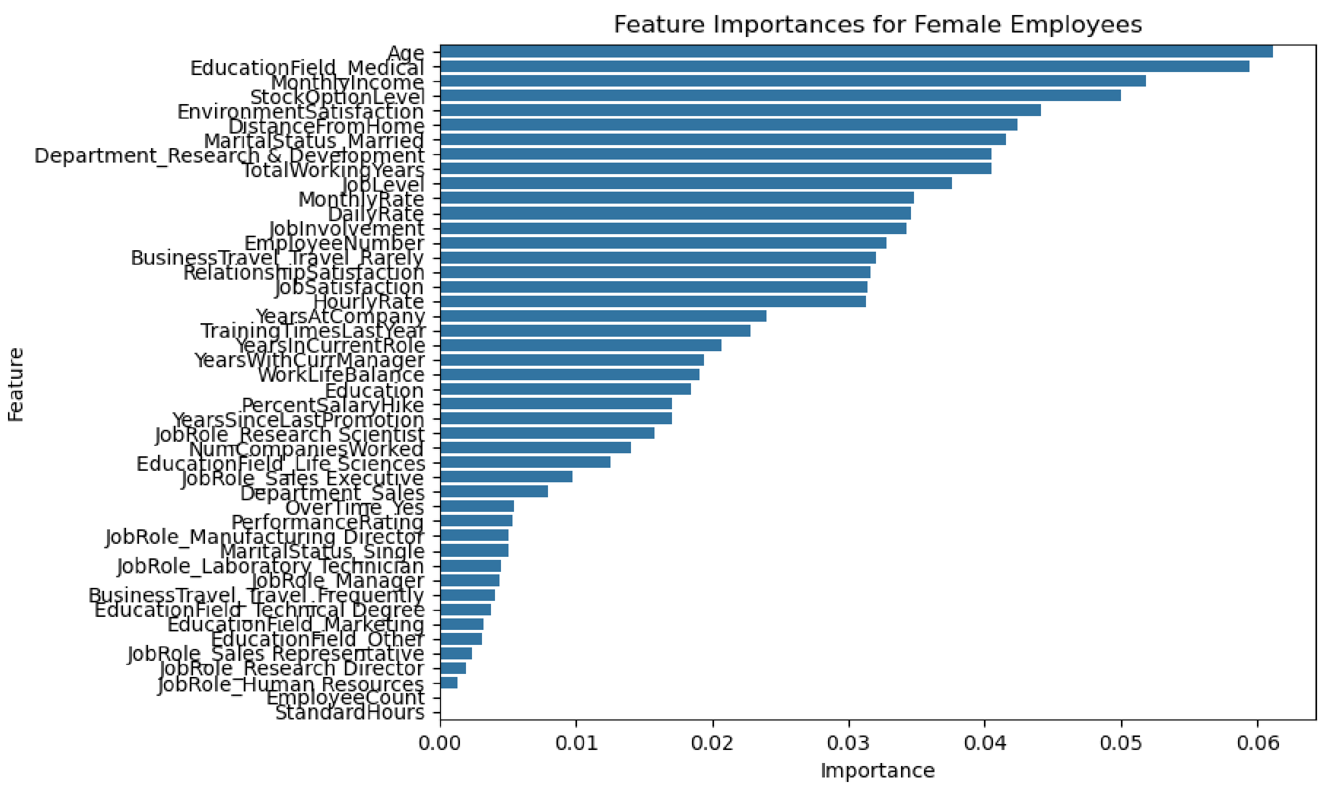

Figure 12. Feature Importance for Male Employee Data

SHAP Value Interpretation:

Figure 13 shows the post hoc analysis of the model predictions using SHAP (Shapley Additive ExPlanations). The SHAP values provide an understanding of each feature's contribution to the probability of attrition. The findings revealed that from the gender perspective, women have a lower propensity of desire to turn away from their jobs provided the organizations offer them relatively high monthly remunerations and provided these women live close to their homes more so than men. This result strengthens the significance of this feature and enhances the insight into the models' thinking processes.

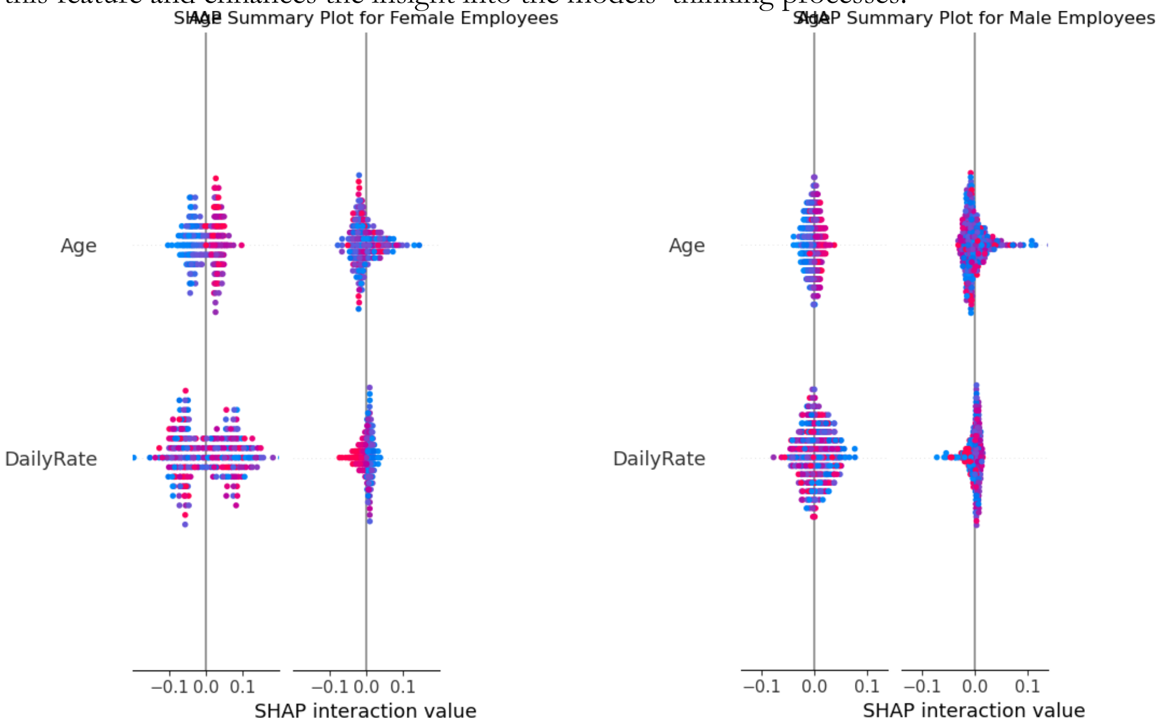

Figure 13. SHAP Values for Model Predictions

Class distribution and attrition trends:

Figure 14 displays the trends related to attrition, job type, and distance from home. We also found that employees who had to travel long distances to work and those with low wages were more likely to experience turnover. These findings are consistent with the findings of the feature importance analysis, which indicate that commute time and the employee's pay packages are critical predictors of turnover. Any map insists that the complicated commutation dilemmas and the questions of remuneration are the critical aspects that must be solved by organizations and that impact staff turnover.

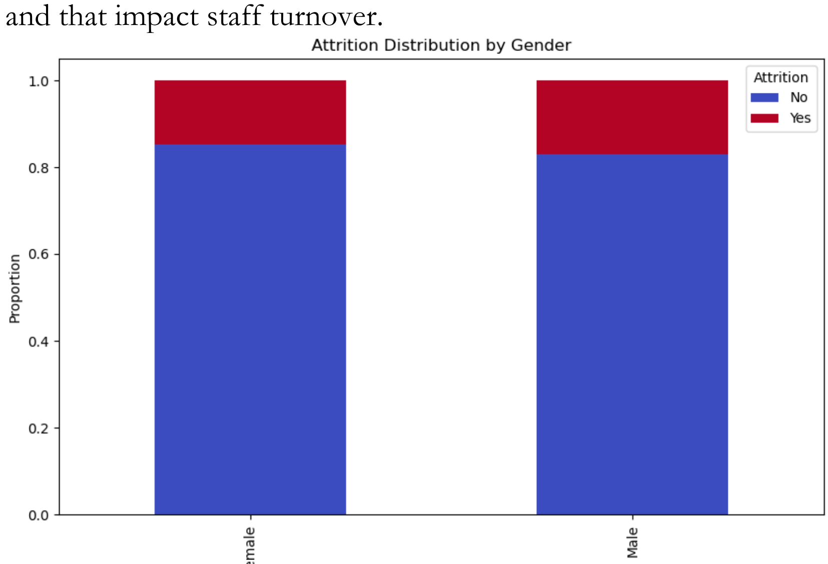

Figure 14. Analyses of Attrition Patterns by Job and Distance from Home

Gender-Based Performance Comparison:

Figure 15 displays performance metrics, showing the difference between the actual and modeled male and female employees. The comparison of results shows that the proposed model is as efficient as the benchmark in terms of high accuracy, precision, and recall. This suggests that the gender-related variables seem to have little bearing on the model's performance. These outcomes are significant in reducing bias in attrition models and ensuring that they work for all possible employee subpopulations.

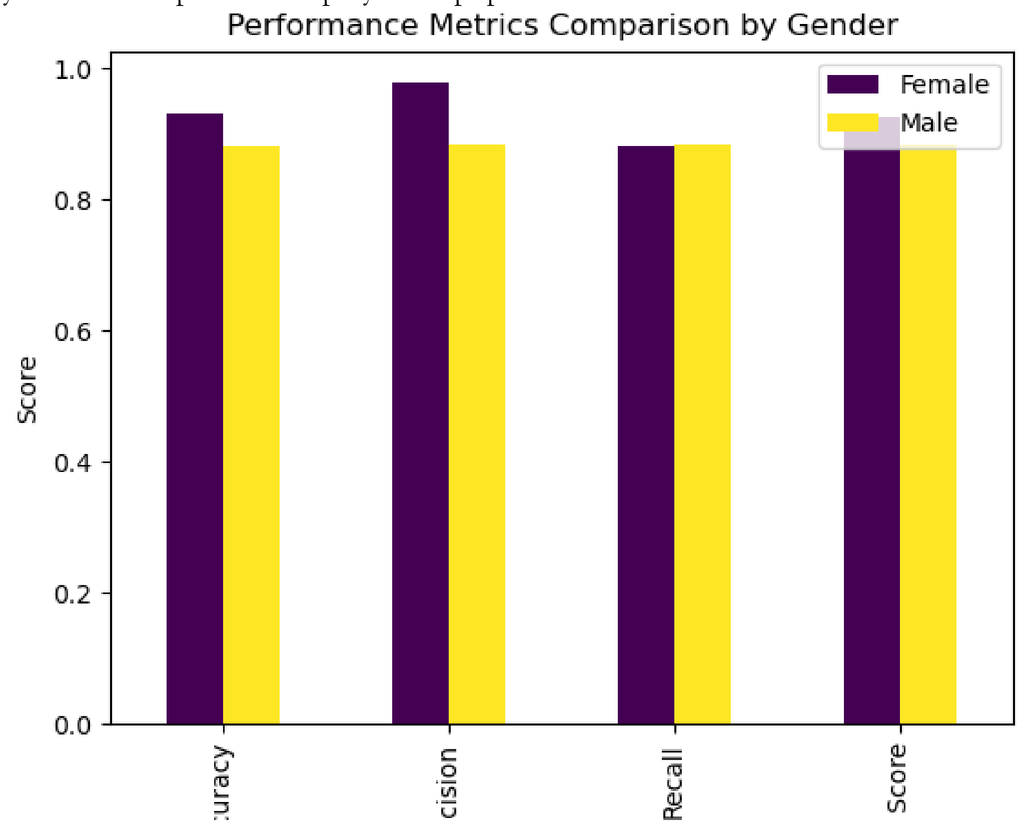

Figure 15. Comparison of Model Performance Metrics by Gender

Discussion:

Pros:

The study provides a comprehensive understanding of potential variables that affect employee turnover rate and contributes insights that will assist the organization in devising strategies for preventing such a problem. Based on the research results, we can make recommendations to alter the ineffective HR practices that contribute to the high turnover rate, thereby ensuring employee satisfaction. This predictive power is useful in preemptive measures because it helps identify and develop strategies to retain good employees.

Cons:

However, there is a gap in terms of generalization of produced results, as they can depend on the type of industry and location of the data. The findings may be potentially limited to industries where the factors behind people's attrition are different or in organizations with dissimilar positions; there may be limits to generalizing the results to other geographic locations of the organization. Moreover, the sample does not represent a high level of variability across the demographics of participants or their organizational occupations, and this could limit the conclusions' generalizability even more. Lastly, the findings are company-specific to IBM and thus may not generalize the conditions within the overall economy or organizations.

Practical implications and recommendations:

The conclusions drawn from this study may be useful for organizations seeking to reduce employee turnover. Structural interventions are possible by targeting some of the main factors that determine the services' use: frequency and one's home distance. Solutions to the problem include providing options such as working from home, decent remuneration that is competitive within the sector, and work satisfaction in a bid to increase retention rates. These facts can be useful in formulating a general management strategy for large staff, thereby preventing turnovers.

Conclusion:

This study employed Random Forest Classifiers on the IBM HR Analytics dataset to classify employee attrition, demonstrating high accuracy, precision, recall, and F1 scores for both male and female employees. Specific preconditions related to turnover were defined, including the level of monthly income, distance from home, and others. SHAP values offered further information on the effects of each of the features on the model's outputs. This evidence backs up the earlier discussion that addressing each factor separately increases the likelihood of employee retention

This paper also opens up opportunities for future research to develop and improve existing models by including more features and using real-world data. We can employ the following strategies to obtain and utilize real-world data.

- Outsourcing with organizations to obtain anonymized employee data
- surveys to gather specific employee experiences and information about the organization.
- Utilizing publicly available data from government and/or industry reports.

Further, examining additional methods and approaches to the algorithms for machine learning or carrying out longitudinal research will give a better understanding of the turnover enigmas and the efficiency of the retention measures.

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