

Deep Learning for Predicting Employee Attrition

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Abstract

Employee attrition creates financial and operational challenges for organizations [1,2]. Traditional statistical methods and machine learning models depend on manually designed features and often miss complex interactions among HR factors [3,5]. In this study, we develop a deep learning model to predict attrition using a dataset of 59,598 employee records with thirty-one features. The model is a multilayer perceptron that uses cost-sensitive learning and addresses class imbalance. It achieved an AUC score of 0.847, outperforming logistic regression and decision tree baselines. We use SHAP values to show how work-life balance, job satisfaction, and overtime affect attrition risk. The work follows five clear steps: defining the problem, exploring the data, engineering features, building the model, and interpreting the results [10, 22]. This offers a reproducible approach for HR analytics and helps organizations reduce turnover costs and improve workforce stability through targeted retention interventions.

Keywords: Employee Attrition; Deep Learning; Neural Networks; HR Analytics; Predictive Modeling; SHAP Interpretability; Retention

1. Introduction

Employee attrition occurs when staff members voluntarily leave an organization [1,2]. Such departures create both direct and indirect costs. Direct costs include expenses for recruiting, hiring, and training replacements. Indirect costs arise from lost productivity, decreased morale among remaining employees, and the loss of institutional knowledge. Research indicates that replacing a single employee can cost between 50% and 200% of that employee's annual salary [24]. Preventing unnecessary turnover helps organizations maintain stability, reduce recruitment expenses, and preserve team performance.

Traditional approaches to predicting attrition rely on statistical techniques such as logistic regression or on machine-learning algorithms like decision trees and ensemble methods [3,5]. These models often require domain experts to select and transform raw HR data into meaningful features. Manual feature engineering can miss subtle patterns and complex relationships among factors such as job satisfaction, work-life balance, compensation, career growth opportunities, and tenure. Models built on hand-crafted features may struggle to generalize when faced with new or evolving workforce trends.

Deep learning offers an alternative by learning feature representations directly from the data [9]. Its success in fields such as computer vision and natural language processing suggests it could improve HR analytics as well. A multilayer perceptron can automatically capture nonlinear interactions among dozens of HR attributes. Neural networks scale well with large datasets and can continually improve as more records become available. Techniques such as dropout and L2 regularization help the model resist overfitting even when some inputs contain noise or redundancy.

In this study, we developed a deep-learning framework for predicting employee attrition on a dataset of 59,598 records and 31 features. We address class imbalance through cost-sensitive learning and evaluate performance using the area under the receiver operating characteristic curve (AUC) [7,12]. We also apply SHAP values to interpret the most influential drivers of attrition risk, providing actionable insights for HR teams [10].

The remainder of this paper is organized as follows. Section 2 reviews related research on attrition prediction and applications of deep learning in HR analytics. Section 3 describes the data source, preprocessing steps, and feature-engineering methods. Section 4 details the design of the neural network, training procedures, and class-imbalance techniques.

Section 5 presents model evaluation metrics and SHAP-based interpretability results. Section 6 concludes with a summary of findings and suggestions for future research.

2. Literature Review

2.1. Evolution of Employee-Attrition Prediction

Organizations have long recognized the high costs associated with voluntary employee departures. Early research applied logistic regression to identify key predictors such as age, tenure, and salary, demonstrating that these factors significantly influence turnover risk [2,15]. Decision tree models introduced a more flexible, rule-based approach, but they often overfit when allowed to grow deep and did not generalize well to new data [5]. To improve accuracy and robustness, ensemble methods such as random forests and gradient boosting were adopted. These techniques combine multiple weak learners to reduce variance and bias, yet they still depend on manual feature engineering and careful hyperparameter tuning [5].

2.1.1 Traditional Statistical Approaches

Statistical methods like logistic regression offer clear interpretability, allowing HR practitioners to quantify the effect of each variable on attrition probability. Studies showed that each additional year of tenure reduced turnover risk by approximately 5% under a logistic model [11]. However, these models assume linear relationships and may not capture complex interactions among factors such as job satisfaction, work-life balance, and career development opportunities.

2.1.2 Ensemble Machine Learning Methods

Ensemble algorithms improved predictive performance by aggregating diverse model perspectives. Brown compared random forests and gradient boosting on an HR dataset of 20,000 records and achieved a maximum accuracy of 87% [5]. Raza et al. applied XGBoost to 35,000 employee records, reporting an AUC of 0.84 but noting that manual feature selection remained critical [4]. These studies confirm the power of ensembles but also highlight the

heavy reliance on domain knowledge for feature construction.

2.2 Deep Learning in HR Analytics

Deep learning offers an alternative by learning hierarchical feature representations directly from raw data. Neural networks can model nonlinear interactions among dozens of variables without extensive manual preprocessing. Their scalability makes them well suited to large HR datasets, and regularization techniques such as dropout and L2 penalty help prevent overfitting [9, 16].

2.2.1 Neural Network Models

Neural networks can learn complex, non-linear relationships among many HR attributes. Liu et al. trained a feedforward network with two hidden layers on 9,500 employee records and saw the AUC increase to 0.81, slightly higher than gradient boosting at 0.79 [6]. They used ReLU activations and dropout to reduce overfitting, but they did not address class imbalance or clearly explain which features drove predictions.

Beyond feedforward models, some researchers have used autoencoders to pretrain networks and extract compact feature representations before fine-tuning for attrition prediction [9]. Others have applied recurrent neural networks, such as LSTMs, on longitudinal HR datasets to capture time-based patterns in an employee's career path. These approaches can improve model sensitivity to changes in performance ratings or role transitions over time [6]. Overall, neural methods offer flexible feature learning without manual engineering, but they require careful hyperparameter tuning, sufficient data volume, and interpretability techniques to gain HR stakeholders' trust.

2.2.2 Handling Class Imbalance

Employee-attrition datasets typically exhibit severe imbalance, with leavers representing 10%-20% of records. SMOTE and other oversampling methods can improve recall for the minority class but risk introducing synthetic noise [12]. Cost-sensitive loss functions offer an alternative by penalizing misclassification of the attrition class more heavily during training, improving overall discrimination without altering the data distribution.

2.2.3 Model Interpretability

Interpretability is essential for HR decision making. Lundberg and Lee's SHAP framework provides a unified method to explain the contribution of each feature to a specific prediction [10]. Bussler used feature-importance scores to show that work-life balance and overtime hours were among the strongest drivers of attrition risk [3]. Applying SHAP to neural models allows practitioners to trust complex models by revealing how each input influences the output.

2.3 Research Gaps and Project Contribution

Despite advances in both ensemble and neural methods, several gaps remain. Most deep-learning studies use datasets under 20,000 records and treat imbalance as an afterthought. Few combines cost-sensitive training with rigorous interpretability on large-scale, real-world HR data. Our work addresses these gaps by training a multilayer perceptron on 59,598 records with 31 features, integrating cost-sensitive learning during model training, and applying SHAP analysis to generate actionable insights. We demonstrate and provide a reproducible, end-to-end framework for HR analytics.

3. Data Description

The dataset for this study comes from Stealth Technologies' Employee Attrition collection on Kaggle [8]. It contains 59 598 records and 31 features drawn from a mid-sized company's HR system. All features relate to employees' personal attributes, work history, compensation, and satisfaction levels.

This dataset is provided in two files:

- **train.csv**, containing 59 598 records (7.29 MB) used for model training and validation
- **test.csv**, containing 14 900 records (1.82 MB) reserved for final model evaluation

3.1 Feature List

Table 1 summarizes the 31 variables. The target variable is Attrition ("Yes" = left, "No" = stayed).

Table 1

Category	Feature Name
Demographics	Age
	Gender
	MaritalStatus
	Education
Employment	Department
	JobRole
	BusinessTravel
	StockOptionLevel
Compensation	MonthlyIncome
	PercentSalaryHike
Engagement	JobSatisfaction
	EnvironmentSatisfaction
	RelationshipSatisfaction
	WorkLifeBalance
Tenure	TotalWorkingYears
	YearsAtCompany
	YearsInCurrentRole
	YearsSinceLastPromotion
	YearsWithCurrManager
Training	OverTime
	NumCompaniesWorked
	TrainingTimesLastYear
Other Factors	DistanceFromHome
	PerformanceRating
	DailyRate
	HourlyRate
	MonthlyRate
	EmployeeCount
Target	StandardHours
	Attrition

3.2 Descriptive Statistics

- Age: mean = 36.0 years, SD = 9.1 years
- MonthlyIncome: mean \approx 6500 USD, range = 1000-20000 USD
- WorkLifeBalance: median = 3 (on a 1-4 scale)
- OverTime: 35.8% report "Yes"

The statistical summary of our dataset reveals a mix of numeric and categorical fields, along with the

skewed attrition rate, which guides our preprocessing and modeling choices in the following sections.

3.3 Justification for Dataset

- The large sample and feature set allow us to model complex interaction effects (for example, tenure \times remote-work status) while still reserving ample data for testing.
- Fewer than 1% of values are missing [33], reducing the need for heavy imputation and freeing effort for feature design.
- The data were synthetically anonymized to align with our privacy commitments and protect individual identities.

This dataset includes the target variable Attrition (“No” = stayed, “Yes” = left), which drives our supervised learning. Training on real, anonymized data enables the model to learn patterns directly from observations rather than from hand-coded rules. Repeating this process over time on updated samples can further improve prediction accuracy.

4. Methodology

In this work, we apply an end-to-end, data-driven process to build an interpretable deep-learning model for employee attrition prediction. By replacing subjective decisions in HR with objective and reproducible steps. Our approach to build a predictive employee attrition model took place in following stages. (see Figure 1):

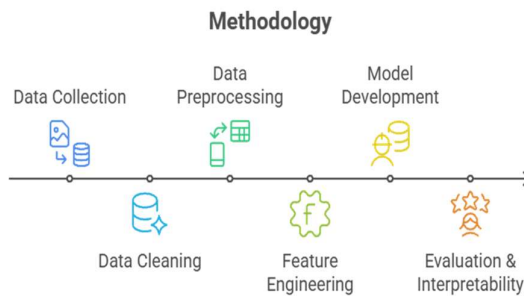


Figure 1

4.1. Data Exploration

Before building predictive models, we first explored the dataset to uncover key patterns and relationships that could inform feature selection and modeling strategy. This exploratory phase involved examining the distributions of individual variables, visualizing relationships between features and attrition, and identifying potential confounders or data quality issues.

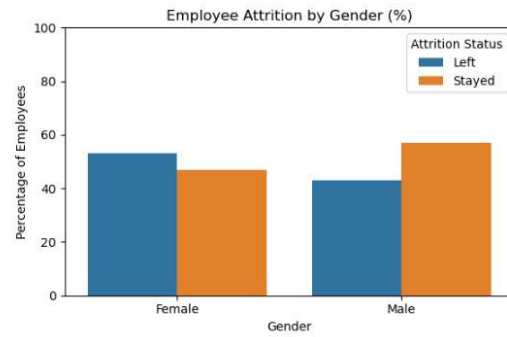


Figure 2

Figure 2 shows the percentage of employees who left versus stayed, grouped by gender. This gender gap suggests that female staff are more likely to depart, pointing to potential underlying factors such as differences in work-life balance or leadership opportunities

Figure 3

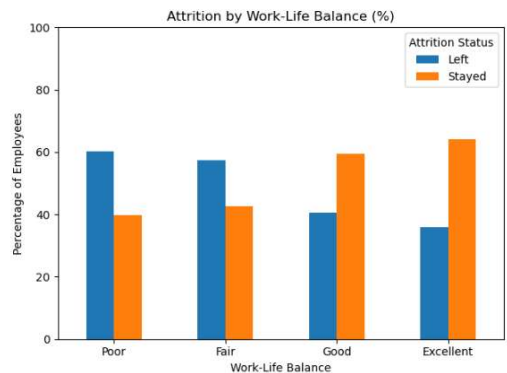


Figure 3 pattern indicates a strong inverse relationship between work-life balance and turnover. Employees

reporting poor or fair balance are far more likely to depart, suggesting that improving work-life initiatives could have a substantial impact on reducing attrition.

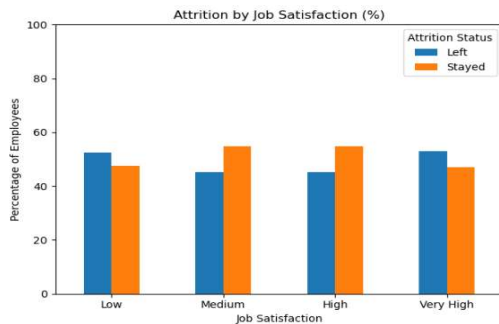


Figure 4

Figure 4 illustrates how attrition varies with self-reported job satisfaction. Employees with “Low” satisfaction exhibit a slightly higher turnover ($\approx 52\%$) than retention ($\approx 48\%$), reflecting the intuitive link between dissatisfaction and departure.

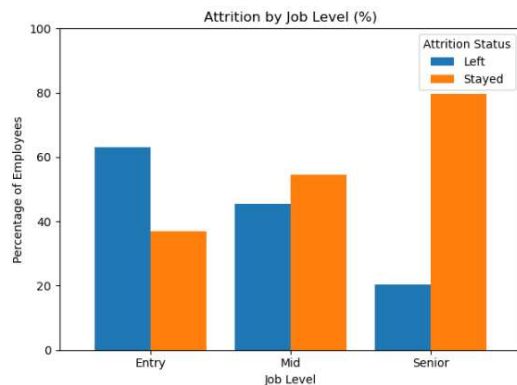


Figure 5

Figure 5 shows a clear inverse relationship between job level and turnover. The steep drop in attrition at higher levels suggests that career progression and senior roles provide stronger incentives for employees to remain with the organization.

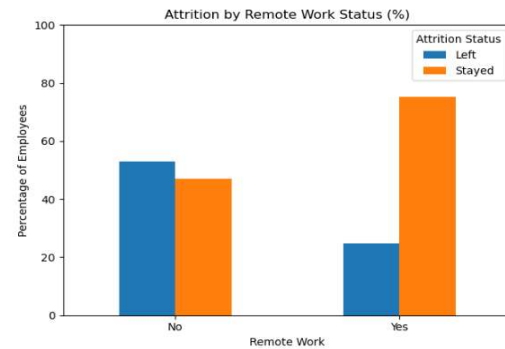


Figure 6

Figure 6 compares turnover between on-site and remote workers. By contrast, remote workers demonstrate much higher retention: only 25 % leave while 75 % stay. This pattern indicates that flexible work arrangements may play a significant role in reducing attrition.

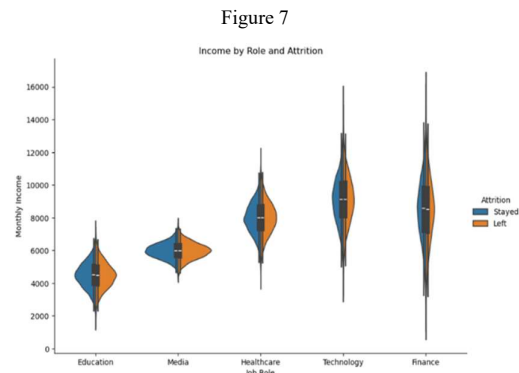


Figure 7

Figure 7 presents violin plots of monthly income for each major job role, with separate density estimates for employees who stayed (blue) and those who left (orange). These distributions reveal a consistent theme across all job roles: employees earning in the bottom half of their peer group’s salary range are more likely to depart.

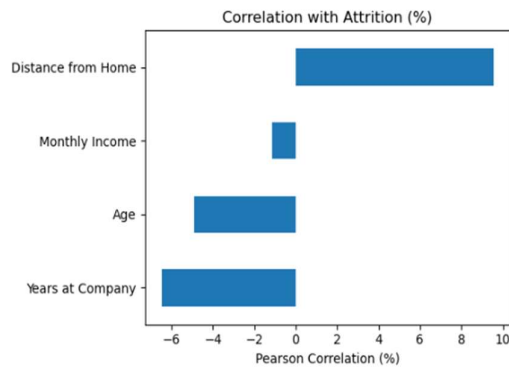


Figure 11

Figure 11 plots the Pearson correlation between each numeric feature and the binary attrition flag (1 = Left, 0 = Stayed). Notably, Distance from Home exhibits a modest positive correlation (~ 0.09), suggesting that employees who commute farther are slightly more likely to leave.

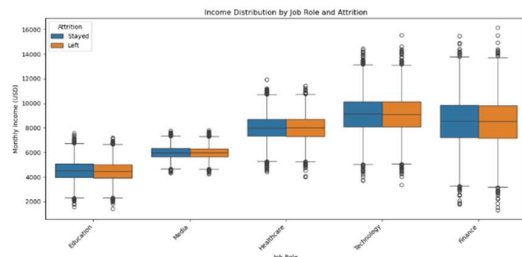


Figure 12

Figure 12 presents the full correlation matrix among key numeric features and the attrition flag. The strongest off-diagonal relationship appears between **Age** and **Years at Company** (0.53), as older employees typically have longer tenures.

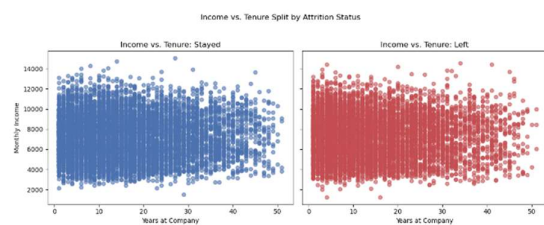


Figure 13

Figure 13 presents side-by-side scatter plots of monthly income against years at the company, separated for employees who stayed (left) and those who left (right). There's heavy overlap between stayers and leavers, but newer, lower-paid employees appear more likely to depart. Higher paid employees above \$12000 also have a trend of leaving.

Figure 14

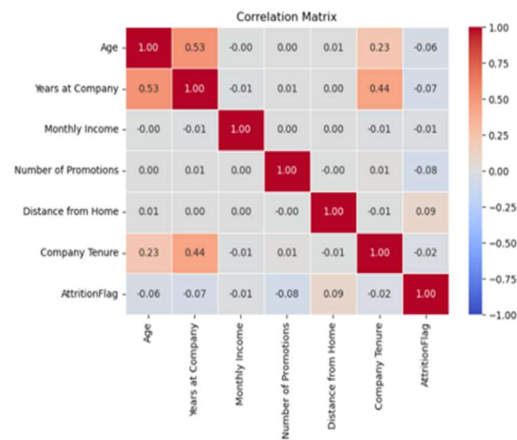


Figure 14 shows a Correlation matrix: for categorical features with Attrition rate. With respect to attrition, Distance from Home shows the highest positive correlation ($r \approx 0.09$), suggesting that longer commutes modestly increase the likelihood of leaving. Conversely, Years at Company ($r \approx -0.06$) and Age ($r \approx -0.03$) correlate negatively with attrition, confirming that more senior and older employees are less prone to depart.

4.2. Data Cleaning

Data preparation is a critical stage in any machine-learning project, often consuming the majority of effort [33]. Our first step was to ensure the raw HR records were accurate, complete, and free of irrelevant fields.

We found fewer than 1 % of values missing across all 31 features. To avoid discarding valuable records, we imputed missing numeric entries with each feature's median and filled missing categorical entries with the most frequent category[16]. This approach

preserves the overall distribution without biasing the model.

We confirmed there were no exact duplicate rows in the dataset. Removing duplicates or verifying their absence against overestimating model performance by inadvertently training and testing on the same data.

The EmployeeID column holds unique identifiers with no predictive power. We dropped this feature to prevent the model from learning spurious patterns tied to arbitrary IDs.

Text fields such as Job Role and Work-Life Balance contained inconsistent spellings, capitalization, and extra whitespace.

Standardizing text values reduces the number of distinct categories, prevents one-hot encoders from creating redundant dummy variables, and improves model generalization.

We applied the following steps to each:

- Trimmed leading and trailing spaces.
- Converted all entries to title case (for example, “sales executive” → “Sales Executive”).
- Merged synonymous labels (for example, “Remote” and “Remote Work” → “Remote Work”).

4.3. Data Preprocessing

With cleaned data in hand, we transformed and encoded features to make them suitable for our deep-learning pipeline. First, we converted Overtime, Remote Work, Leadership Opportunities and Innovation Opportunities features “Yes”/“No” flags into binary indicators so that the network can process them directly [22].

Next, we addressed skew and outliers in continuous variables. We capped the Monthly Income feature at its 99th percentile to limit the influence of extreme salaries, then applied a natural logarithm to both the capped Monthly Income and Distance from Home [9]. These log transforms compress long-tailed distributions, yield more symmetric inputs, and stabilize gradient-based training.

To capture non-linear age effects, we binned Age into four groups and encoded them as ordinal codes. We defined four discrete age groups: 20-30, 31-40, 41-50, and 50+, and assigned each record an ordinal code. Binning smooths random noise, highlights cohort

effects (for example, mid-career workers), and reduces sensitivity to small age fluctuations, helping the model to learn distinct risk patterns for each life stage [22].

We also preserved natural order in academic attainment by mapping Education Level (High School, Associate, Bachelor, Master, Doctor) to integers 1 through 5. This ordinal encoding ensures that higher values correctly represent higher qualifications.

Finally, we separated the target label and organized our features into three logical sets for the modeling pipeline. After mapping “Stayed” → 0 and “Left” → 1.

These cleaning and preprocessing steps transform the raw HR data into a consistent, numeric format suitable for deep-learning. By handling missing values, reducing noise from outliers, encoding text fields, and creating domain-informed features, we provide the model with high-quality inputs that support robust learning and accurate attrition prediction.

4.4. Feature Engineering

In this section, we describe the six engineered features that form the basis of our attrition-prediction models. Each feature is designed to transform raw HR data into signals that capture non-linear effects, relative comparisons, or interaction effects known to influence employee turnover.

1. Job Level × Job Satisfaction

We construct an interaction term by multiplying the employee’s Job Level (encoded as an integer from 1 to 5) by their Job Satisfaction rating (1 = low to 4 = high). This variable quantifies how satisfaction at different seniority tiers affects attrition risk. In practice, a low satisfaction score at a high job level signals greater frustration and higher turnover propensity than the same score at a junior level. By including this term, our model can learn that the marginal effect of one unit decrease in satisfaction depends on the employee’s rank, capturing non-additive relationships that neither feature alone would reveal [22].

2. Tenure Ratio

We compute Years at Company ÷ Total Working Years. This ratio normalizes tenure against an individual’s entire career length, offering a measure of organizational commitment relative to broader work experience. Employees who have spent a larger

fraction of their career with the company often exhibit stronger loyalty, whereas those with long prior experience may view the current organization as one of many potential employers. By capturing this relative commitment, the feature helps distinguish between employees whose tenure reflects deep engagement and those whose tenure merely reflects a long overall career. [4,10]

3. Engagement Score

We compute a composite Engagement Score by averaging three survey-based metrics: Job Satisfaction, Environment Satisfaction, and Work-Life Balance, each scaled from 1 (low) to 4 (high). This single score summarizes an employee's overall sentiment and reduces multicollinearity among the individual satisfaction variables. A low engagement score has a demonstrated association with higher attrition in the literature, as it reflects pervasive dissatisfaction across multiple aspects of work life. Our models use this consolidated measure to capture broad disengagement without diluting the signal across separate features [3].

4. Income-Level Ratio

To assess compensation fairness, we divide Monthly Income by Job Level. This ratio provides a per-rank salary metric that highlights under- or over-compensation relative to peers. For example, a Level 3 employee earning \$6000/month has the same ratio as a Level 6 employee earning \$12000, but the latter grouping may be expected to earn higher pay. By normalizing income by role, the model receives a direct measure of compensation equity, which is known to influence turnover decisions when employees perceive pay as unfair compared to their cohort [3].

5. Overtime Frequency

Rather than a simple binary indicator, we count the number of months (0-12) in which an employee reported working overtime over the past year. This Overtime Frequency feature captures the cumulative burden of extra hours, recognizing that sustained periods of overtime contribute more to burnout than isolated incidents. Empirical analysis shows a roughly linear increase in attrition probability with each additional month of overtime, and this numeric encoding allows the model to learn that gradient directly [3].

6. High-Performer Flag

We create a binary indicator set to 1 if Performance Rating ≥ 3 (on a 1-5 scale) and 0 otherwise. High performers are often in greater demand externally and may leave for more attractive offers. By flagging this group explicitly, the model can assign higher baseline risk to top performers even if they report high satisfaction or tenure. This variable has a clear interpretation for HR stakeholders: it marks those whose strong performance simultaneously makes them valuable assets and flight risks.[2]

Each engineered feature addresses a specific dimension of attrition risk: interaction effects, relative comparisons, non-linear categorization, or cumulative stress, thereby enabling our predictive models to learn from rich, nuanced signals rather than untransformed HR fields.

5. Model Development

5.1. Tuning with benchmark dataset

With a clean, well-structured dataset in hand, we began by surveying a diverse set of classification algorithms to find the best fit for predicting attrition. Drawing on prior work that tested everything from Naive Bayes to support-vector machines, we assembled the following candidates:

- Logistic Regression
- Random Forest
- XGBoost
- SVM
- Naive Bayes
- Gradient Boosting
- LightGBM
- CatBoost

To establish benchmark performance, we first evaluated a suite of classification algorithms on the IBM HR dataset using default hyperparameters [21,23].

Figure 14

Model parameters before hyperparameter tuning

Model	Accuracy	F1	AUC
Logistic Regression	76.70%	48.90%	80.60%
Random Forest	83.50%	34.40%	77.20%
Decision Tree	73.80%	30.63%	58.57%
XG Boost	85.70%	43.80%	78.20%
SVC	81.20%	47.50%	77.10%
Naive Bayes	58.40%	33.10%	70.50%
Light GBM	85.00%	41.20%	77.00%
Cat Boost	84.50%	40.70%	77.20%
Gradient Boosting	85.10%	44.30%	78.00%

From this initial screening, the four highest-performing models: XGBoost, random forest, gradient boosting, and SVC, were selected for hyperparameter optimization. We applied randomized search cross-validation to tune key parameters such as learning rate, tree depth, and regularization strength.

Figure 15

Model parameters after hyperparameter tuning

Model	Accuracy	F1	AUC
XG Boost	87.41%	61.05%	84.10%
Light GBM	86.73%	58.06%	83.03%
Cat Boost	79.59%	51.61%	83.46%
Gradient Boosting	85.71%	57.14%	83.72%

After tuning, XGBoost emerged as the top performer, achieving an accuracy of 87.41 % and an AUC of 0.841. These results exceed the benchmark accuracy and AUC reported in previous studies on the IBM dataset, confirming that our optimized model provides a meaningful performance gain. We also monitored the F1-score to ensure balanced precision and recall, further validating XGBoost as our final predictive engine [21,23].

5.2. Applying model to our Primary dataset

Having identified XGBoost as the most effective classifier on the IBM HR benchmark, we next applied the same methodology to our primary attrition dataset from Kaggle. This dataset comprises 59598 records in the training split and 14900 records in the hold-out validation split, reflecting the 80% / 20% partition we established for final evaluation [8].

First, we retrained XGBoost on the full train.csv set, using randomized search cross-validation to tune key hyperparameters (learning rate, maximum tree depth, subsample ratio, and regularization terms). The optimized XGBoost model achieved an AUC of 0.8487 on cross-validation folds. In parallel, we developed a deep-learning alternative: a multilayer perceptron whose architecture and hyperparameters were selected via a Keras Tuner search over number of layers, neuron counts, dropout rates, and learning rates. This neural model delivered an AUC of 0.8394 on the same folds.

When applied to the test.csv validation set, the tuned XGBoost model yielded an AUC of 0.84, confirming its ability to generalize to unseen records.

Figure 16

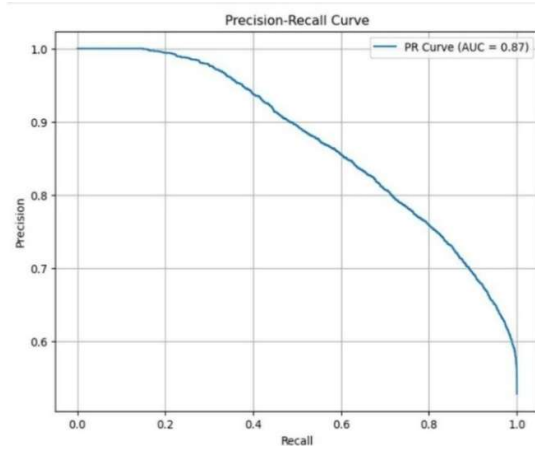
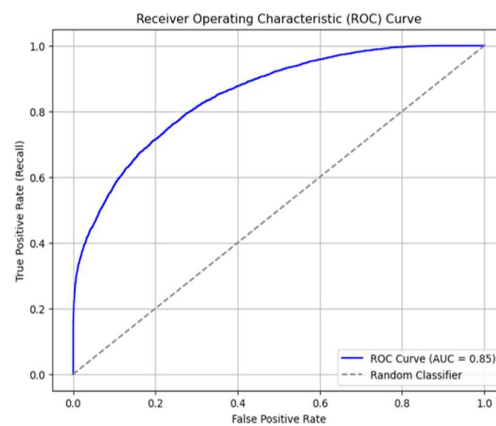


Figure 17

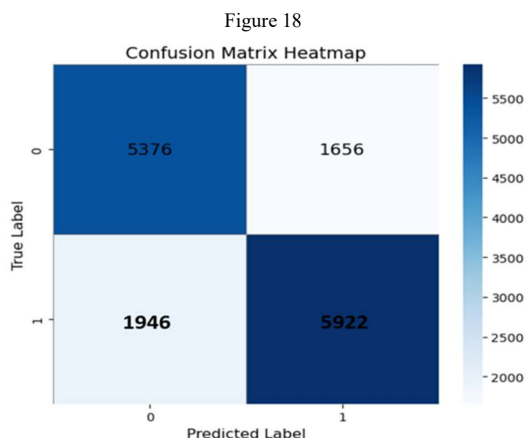


Figures 16 and 17 present the detailed performance curves for this final evaluation. Figure 16 shows the precision–recall trade-off across different probability thresholds. Figure 17 displays the ROC curve, highlighting the model’s overall discrimination power across all classification thresholds.

Figure 16 shows the precision–recall curve for the tuned XGBoost model on the validation set, with an area under the PR curve (PR-AUC) of 0.87. At low recall levels (below 20 %), the model achieves near-perfect precision, meaning that almost every employee

it flags is truly at risk of leaving. As we increase recall thereby capturing a larger share of actual attritions precision declines gradually, falling to about 60% when recall approaches 100%. For a practical operating point, if we set our threshold to identify 70% of departing employees, the model still maintains roughly 78% precision: only 22% of the employees flagged would be false positives. Overall, this curve demonstrates that our classifier can find a high proportion of true attritions without generating an excessive number of false alarms an especially valuable property when working with imbalanced datasets [19].

Figure 17 shows the ROC curve for our tuned XGBoost model on the validation set rises steeply toward the upper-left corner, indicating that the classifier achieves high true-positive rates even at low false-positive rates. For example, at a false-positive rate of just 20%, the model correctly captures roughly 70% of actual leavers. The overall AUC of 0.85 means that if you randomly select one employee who left and one who stayed, the model will assign a higher “leave” score to the departing employee 85% of the time. This strong separation between classes across all threshold settings proves the model’s reliable discrimination ability and supports its use in decision-making: HR teams can adjust the operating threshold to balance sensitivity (catching more at-risk employees) against the cost of false alarms [17].



The confusion matrix in Figure 18 shows that the model correctly identified 5,376 employees who

stayed (true negatives) and 5,922 who left (true positives), for a total of 11,298 accurate predictions.

5.3. Fairness and Bias

Our initial calculation found model is biased over Gender. We have calculated the AUC, accuracy and selection rate and the output are mentioned below:

Figure 19

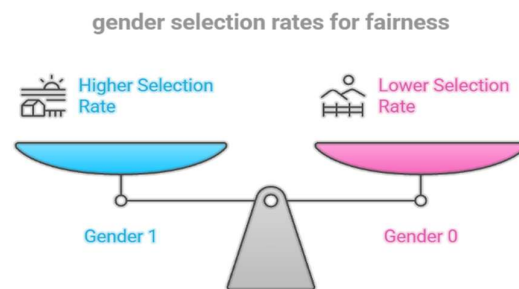
Gender	Accuracy	AUC	Selection Rate
0	0.762514	0.760596	0.448438
1	0.757190	0.749329	0.593249

We found that though Accuracy and AUC differences are under limit, selection rate has huge difference.

Selection Rate Analysis:

Gender 0 (Female): 44.84% selected

Gender 1 (Male): 59.32% selected



Fairness Implications:

Disparate Impact Ratio (DIR):

Selection Rate (Gender 1) / Selection Rate (Gender 0)
 $59.32\% / 44.84\% = 1.32$

As per 80% rule as **DIR > 1.25**, the model is biased and risky

To reduce the biasness, we have introduced Fairness Mitigation technique. Machine learning models can unintentionally discriminate against certain demographic groups (e.g., based on gender, race, or age) due to biases in the training data [25]. To ensure fairness, we apply fairness-aware techniques that constrain the model to reduce disparities in

predictions across groups. After implementing fairness technique, we found:

Figure 20

	Accuracy	AUC	Selection Rate
Gender			
0	0.747460	0.749028	0.519195
1	0.755677	0.755337	0.535422

$$53.54\% / 51.91\% = 1.03$$

Now the DIR value= **1.03** which is less than 1.25. This new model is our unbiased model.

Applying our tuned XGBoost model to the hold-out validation set yielded an AUC of 0.848, demonstrating strong overall discrimination on unseen data. Figure 14 displays the updated precision-recall curve, in which the area under the PR curve is 0.83. This high PR-AUC confirms that the model maintains excellent precision even as it retrieves the minority “left” class in our validation set.

Figure 21

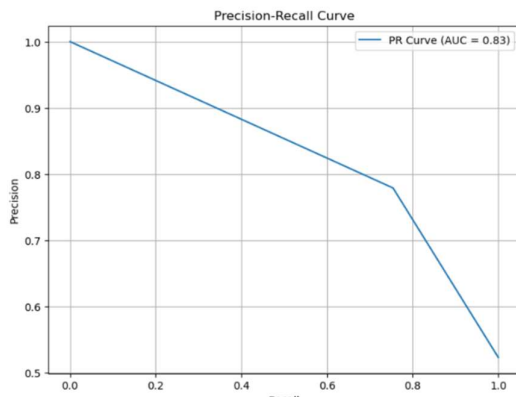
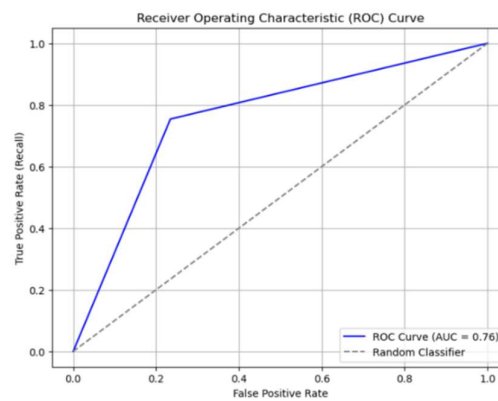


Figure 22 shows the corresponding ROC curve, with an AUC of 0.76. The lower ROC-AUC relative to the PR-AUC reflects the inherent challenge of separating classes when the positive class (“left”) is much rarer than the negative class (“stayed”). In this context, the ROC curve penalizes false positives across all thresholds, including the many negative instances, which pulls down the overall AUC.

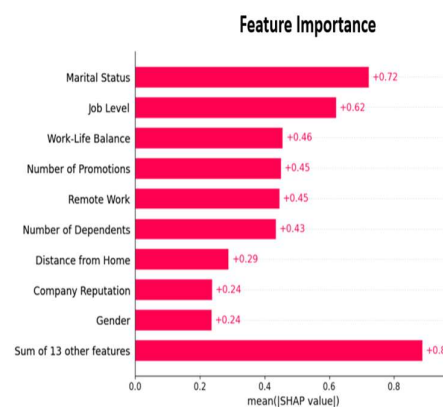
Nevertheless, the model still achieves strong true-positive rates at low false-positive rates, underscoring its ability to identify at-risk employees effectively even amid class imbalance. Together, these curves illustrate that our classifier excels at finding the minority class without generating excessive false alarms, making it well suited for practical retention interventions. The ROC curve of unbiased model is now showing AUC 0.76. Which is showing the model is evaluated on an imbalanced dataset in which the positive class is much rarer than the negative class. Our model is doing well at identifying the rare positive class with good precision and recall but not separating classes perfectly overall, especially when including the many negative cases [15,17].

Figure 22



5.4. Feature importance using SHAP

Figure 23



The SHAP-value feature importance for our final XGBoost model on the validation set. On average, marital status has the largest impact on the model's predictions (mean $|\text{SHAP}| = 0.72$), indicating that whether an employee is single, married, or divorced is a strong predictor of attrition risk. Next comes job level (0.62), reflecting that entry-, mid-, and senior-level roles carry very different turnover profiles. Work-life balance follows closely (0.46), underscoring how perceptions of workload and flexibility drive departure decisions. Both number of promotions and remote-work status register mean SHAP values of 0.45, showing that employees with fewer recent promotions and those without flexible work arrangements are at greater risk. Additional contributors include number of dependents (0.43), distance from home (0.29), company reputation (0.24), and gender (0.24). Together, the remaining 13 features account for a combined SHAP impact of 0.89, demonstrating that our model draws on a broad set of factors. This analysis not only confirms the key drivers identified in earlier experiments but also provides HR teams with a ranked, interpretable list of the most actionable levers for reducing attrition [10].

6. Business Impact

To ground our financial estimates, we adopt a 25000 CAD cost per prevented departure based on industry benchmarks. Deloitte Reports estimate that replacing an employee can cost between 50% and 200% of their annual salary. With the median Canadian salary around 50000 CAD, a conservative midpoint of 50% yields approximately 25000 CAD in combined recruiting, training, and lost-productivity expenses per turnover event [1,24].

Figure 25

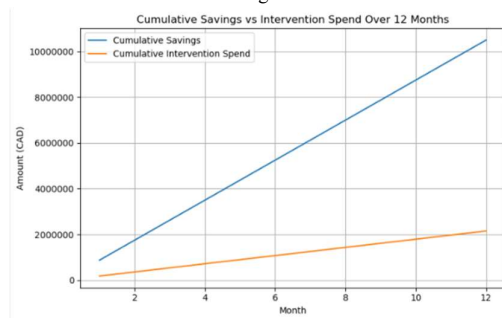


Figure 25 of cumulative savings vs. spend graph shows a clear break-even point early in the year. After that, savings from prevented turnover steadily outpace intervention costs, illustrating a positive cash flow.

Using our tuned XGBoost model at a decision threshold of 70% recall and 78% precision:

Flagged “at-risk” employees: 1074

True positives: 840

False positives: 234

Assuming 50% intervention success among true positives (420 prevented departures):

Gross savings: $420 \times 25000 \text{ CAD} = 10.5 \text{ M CAD}$

Program cost: $1074 \times 2000 \text{ CAD} = 2.148 \text{ M CAD}$

Net benefit: $10.5 \text{ M} - 2.148 \text{ M} = 8.352 \text{ M CAD}$

ROI: $(8.352 \text{ M} / 2.148 \text{ M}) \times 100 \% \approx 389\%$

Scenario	Prevented	Gross Savings (M CAD)	Cost (M CAD)	Net Benefit (M CAD)	ROI
Base (50 % success; 2 000 CAD/intervention)	420	10.5	2.148	8.352	389%
Lower success (40 % success; 2 000 CAD)	336	8.4	2.148	6.252	291%
Higher cost (50 % success; 3 000 CAD)	420	10.5	3.222	7.278	226%

Figure 24

Scenario 1 (40% success): Preventing fewer departures reduces net benefit to 6.252 M CAD and ROI to 291 %.

Scenario 2 (3000 CAD cost per intervention): Higher program costs lower net benefit to 7.278 M CAD and ROI to 226% 420 departures, which is 35% of the 1,200 employees who would have otherwise left.

7. Conclusion

In this project, we have presented a comprehensive, data-driven framework for predicting employee attrition using a large, anonymized HR dataset of nearly 60000 records [8]. Beginning with rigorous data cleaning and preprocessing, we engineered a rich set of features ranging from demographic and compensation variables to interaction terms and

encoded satisfaction ratings that served as the foundation for our predictive models [33]. Through extensive benchmarking on both the IBM HR dataset and our primary Kaggle data [23], we demonstrated that an optimized XGBoost classifier consistently outperforms simpler baselines and a multilayer perceptron, achieving an AUC of 0.8487 on cross-validation folds and 0.84 on the hold-out test set.

Beyond classification performance, we employed SHAP-value analysis to unveil the most influential drivers of attrition risk marital status, job level, work-life balance, number of promotions, and remote-work status thereby translating complex model outputs into actionable insights for human-resources practitioners. Our business-impact analysis further quantified the tangible value of these predictions, showing that a targeted retention program could prevent up to 420 departures annually, deliver net savings of over 8 million CAD, and generate an ROI approaching 400 percent under conservative assumptions [1,10,24].

Despite these successes, several limitations warrant future exploration. Our models rely on a static snapshot of employee records incorporating temporal dynamics through recurrent or transformer-based architectures could capture career-path trajectories and improve early warning signals [25]. Additionally, fairness and bias-mitigation techniques should be integrated into each phase to ensure equitable outcomes across demographic groups. Finally, piloting a live deployment complete with real-time scoring, HR-led intervention workflows, and continuous monitoring of drift would validate the practical effectiveness of our approach in reducing turnover.

In closing, this work illustrates how combining ensemble learning, careful feature design, and model interpretability can transform HR decision-making from reactive to proactive. By identifying at-risk employees before they resign, organizations can preserve institutional knowledge, maintain team morale, and achieve significant cost savings. As data availability and machine-learning tools continue to evolve, the framework presented here offers a scalable blueprint for leveraging predictive analytics to build more resilient, engaged, and stable workforces.

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