

The Mechanism of Employee Characteristics on Promotion: Building the Predictive Machine Learning Model

Zhuoning Jin^{1*}, Bo Yu², Tian Zhou³

*¹Faculty of Business and Management, Beijing Normal University-Hong Kong Baptist University
United International College, Zhuhai, China*

²University of California, Santa Barbara, USA

³University of Minnesota, Twin Cities, Minneapolis, USA

**Corresponding Author. Email: jernyjjin@gmail.com*

Abstract: Purpose: This study developed a predictive model based on employee characteristics, analyzes multidimensional data to identify predictive factors of promotion outcomes, and provides data-driven insights for organizations to improve talent management. Methods: Decision tree, random forest, and neural network models were built on the existing dataset (N=54,808). Then, the models' predictive efficacies were evaluated to select the optimal model using several methods. Results: The accuracy of decision tree was 85.7%. The accuracy of artificial neural network and random forest model was 93%. For promoted class, random forest had higher precision, while neural network performed slightly better in recall and F1 score. For non-promoted class, both models perform almost identically in precision, recall, and F1 score. Conclusion: Random forest and neural network had good predictive efficacy for employee promotion. If avoiding false promotions is more important (i.e., precision matters more), random forest is the better model. If capturing more promotions is critical (i.e., recall matters more), even at the cost of some false positives, then the neural network is slightly better.

Keywords: employee promotion, HRM, decision tree, random forest, neural network.

1. Introduction

In the past decade, research on employee promotion mechanisms has attracted widespread attention from academia and business management. In service industries such as hospitality, transportation, and retail, employee promotion is not only crucial to personal career development, but also directly affects organizational operational efficiency and customer satisfaction [1]. Many studies have focused on analyzing factors that affect career development, such as employee performance, tenure, and organizational culture [2].

However, despite the abundance of research on factors influencing promotion, how to effectively use data-driven methods to objectively predict employee promotion opportunities remains unclear. Promotion decisions are often based on subjective assessments and seniority rather than transparent and evidence-based criteria [3]. This lack of transparency and objectivity in the promotion process can lead to unfairness, which in turn reduces employee satisfaction and organizational performance. [4].

The purpose of this study is to fill this research gap by developing a predictive model based on employee characteristics. Besides, by analyzing multidimensional data, including education level, work experience, and performance scores, this research also aims to identify which factors are the most predictive of promotion outcomes. The findings will provide organizations with actionable, data-driven insights into promotion decisions, helping to improve the fairness and efficiency of talent management, ultimately increasing operational efficiency and customer satisfaction. [5].

2. Literature Review

Existing literature on employee promotion and career development focuses primarily on the relationship between employee characteristics and job performance. For example, Smith [6] suggests that key factors such as work attitude, skill level, and teamwork are critical determinants of employee performance, particularly in the service industry. However, few studies have examined how these characteristics directly affect promotion opportunities.

Johnson [7] explored the role of employees' leadership and self-motivation in promotion outcomes and concluded that these abilities are very important for employees' career development and promotion. However, much of this research is based on qualitative analyses and lacks the quantitative models necessary for predicting promotion. Furthermore, the majority of studies in this field emphasize factors such as tenure and subjective performance evaluations rather than objective, data-driven criteria [8].

In recent years, the application of machine learning and data analytics in human resource management has gained increasing attention. Chen et al. [9] have demonstrated the role and potential of predictive analytics in predicting employee performance and turnover. However, these studies often focus on performance metrics or job satisfaction and do not specifically address the promotion process. Moreover, the existing models generally lack integration of soft skills such as leadership, communication, and teamwork abilities, which are crucial for promotion decisions [10].

Lee's [11] research emphasizes the importance of transparency in the promotion process, arguing that data-driven, objective methods can significantly reduce bias and improve employee morale. However, in existing companies, there are few pure models used to determine employee promotion opportunities, but existing data models can actually make good use of big data to make objective decisions. Machine learning models such as decision trees and random forests have shown great potential in analyzing complex, multidimensional employee data to identify promotion potential [12]. These models can analyze large data sets to discover hidden patterns and provide actionable insights, enabling organizations to make fairer and more effective promotion decisions.

However, existing research still faces several limitations. Many prediction models are prone to overfitting and therefore have low reliability when applied to new datasets [13]. In addition, the range of features used in existing models is limited, often excluding key factors such as team dynamics, leadership assessment, and adaptability [14]. Therefore, future research should focus on expanding the range of employee characteristics included in promotion models and continuously improving these models to cope with the dynamic nature of labor demand.

By addressing these gaps, this study will contribute to the growing field of data-driven decision-making in human resources, particularly in improving the fairness and efficiency of promotion processes. The insights derived from this study will provide valuable guidance to organizations seeking to implement more transparent and objective promotion strategies, ultimately leading to better workforce management and improved operational performance [15].

3. Methodology

The methodology involves data preparation, exploratory data analysis, model selection, training, and evaluation followed by optimization of the model. Therefore, data preparation has been conducted using Python libraries such as *pandas*, *numpy*, *scikit-learn*, and *seaborn*.

3.1. Data collection and preparation

The dataset includes features of employees that encompass quantitative variables such as age, number of training sessions, average training score, length of service, and previous year rating. It also includes qualitative variables such as department, education, gender, recruitment channel, and awards won. The target variable is binary, denoted as “Is Promoted,” which indicates whether an employee was promoted or not.

Appropriate handling of the missing values has preserved the integrity of the data. For numeric variables, imputation was used targeting the median, while for categorical variables, imputation involved the use of the most frequent values. These steps ensure that model performance will not be compromised due to missing data. Missing value treatment was performed using the *SimpleImputer* class of the *scikit-learn* package. After handling the missing values, the data was split into training, validation, and test sets using an 80/20 split. Subsequently, the validation and test sets were each split in equal halves for model tuning and final evaluation, respectively. The splitting was performed using the function `train_test_split` from *scikit-learn*.

3.2. Exploratory data analysis (EDA)

We first conduct EDA to identify the relationship between various features and determine the most influential variables related to an employee's promotion. The quantitative features were explored interactively with the help of correlation matrices to show how different variables are related. The correlation coefficient r between two variables X and Y is calculated as follows:

$$r_{XY} = \frac{\sum_{i=1}^n (x_i - \bar{X})(y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{X})^2 \sum_{i=1}^n (y_i - \bar{Y})^2}}$$

Quantitative features were described using measures of mean, median, and standard deviation, while categorical features were described in terms of frequency distributions. Through EDA with heatmap, it was found that features like average training score, previous year rating, and no of trainings were highly correlated with promotion.

3.3. Model selection and training

To predict whether an employee is promoted, we test all four Decision Tree Classifier, Random Forest Classifier, and Neural Network models, and then select the best model for subsequent analysis.

3.3.1. Decision tree classifier

A decision tree classifies data by recursively partitioning the data based on feature values, taking into consideration certain criteria such as Gini impurity or entropy to determine the quality of a split. Gini impurity is defined as:

$$G = 1 - \sum_{i=1}^C p_i^2$$

Where p_i is the probability of class i in the node, and C is the number of classes (in this case, two: promoted or not promoted). Another criterion for splitting is entropy, defined as:

$$H = - \sum_{i=1}^C p_i \log_2 p_i$$

Where H is the entropy of the node. The Decision Tree Classifier provided intuitive results for identifying key variables, such as average training score and previous year rating.

3.3.2. Random forest classifier

The general prediction from a random forest is obtained by averaging the predictions from multiple decision trees:

$$\hat{y} = \frac{1}{T} \sum_{t=1}^T h_t(X)$$

Where T is the number of decision trees, and $h_t(X)$ is the prediction from the t -th tree. Each decision tree is trained on a random subset of the data, and a random subset of features is considered for each split.

The random forest model provides feature importance, which helps identify the most critical features for promotion prediction, such as average training score and previous year rating.

3.3.3. Neural network model

Artificial neural networks (ANNs) represent a category of nonlinear models that are extensively utilized in the medical domain. They mimic the architecture of human brain neurons to process data. A key benefit of these networks lies in their capacity to effectively address correlations and interactions among variables, which enhances the informational value derived from each variable [16]. The output y of a neuron can be expressed as:

$$y = f \left(\sum_{i=1}^n (w_i x_i + b) \right)$$

where w_i are the weights, x_i are the inputs, b is the bias, and f is the activation function. Neural networks excel in tasks such as image recognition, natural language processing, and regression analysis.

3.4. Model evaluation

All models were evaluated based on four key metrics: accuracy, precision, recall, and F1-score. These metrics provide insight into the models' performance in classifying both positive (promoted) and negative (not promoted) cases.

Accuracy: Measures the proportion of correctly classified instances.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Precision: Measures the proportion of true positives among all positive predictions.

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall: Measures the proportion of true positives among all actual positives.

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1-score: The harmonic mean of precision and recall.

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Where TP, TN, FP, and FN refer to true positives, true negatives, false positives, and false negatives, respectively.

3.5. Model optimization

Hyperparameter tuning was conducted using RandomizedSearchCV from the scikit-learn library for the Random Forest and AdaBoost models. The optimization aimed to identify the best model parameters (such as the number of estimators, learning rate, max depth) to maximize accuracy and minimize overfitting.

For Random Forest, parameters such as the number of trees ($n_{\text{estimators}}$) and the maximum depth of the trees (d_{max}) were optimized to achieve better performance. Similarly, for AdaBoost, the learning rate (α) and the number of weak learners ($n_{\text{estimators}}$) were tuned to improve model accuracy. In the final step, we choose to focus on Decision Tree and Random Forest model building.

4. Results

The result of the research provides a detailed analysis and performance of various machine learning models, with a special focus on the Random Forest algorithm, in predicting employee promotion from various employee characteristics. These characteristics are not limited to quantitative factors such as average training score, previous-year rating, and number of trainings, as well as qualitative ones such as department, education level, and recruitment channel. Standard metrics that comprise classification include accuracy, precision, recall, and the F1 score.

4.1. Exploratory data analysis

The features under review (Table1) are the number of trainings, rating of the previous year, length of service, average training score, and age. The number of trainings ranged from 1 to 10, with a mean of 1.25 and a median of 1. The positive skewness of 3.45 suggested that the majority of employees have completed only a few trainings. The average training scores ranged widely from 39 to 99, with a mean of 63.71 and a median of 60.0, indicating variability in employee performance in training programs.

Table 1: EDA descriptive statistics

Feature	Max	Min	Mean	SD	Median	Skewness
No of training	10	1	1.25	0.61	1	3.45
Previous year rating	5	1	3.33	1.26	3	1.26
Length of service	37	1	5.87	4.27	5	1.74
Avg training score	99	39	63.71	13.52	60	-
Age	60	20	34.8	7.66	33	1.01

Performance ratings over the past year ranged from 1 (low) to 5 (high), with an average of 3.33 and a median of 3.0. This suggested that for many employees, performance during the last year was middle-of-the-road. Length of service ranged from 1 to 37 years, with an average of 5.87 years and a median of 5 years, indicating reasonable retention. The analysis provided an initial look at possible predictors of promotion, where the mean training score, last year's rating, and the number of trainings were likely to be significant variables.

4.2. Correlational analysis and bivariate analysis



Figure 1: Correlational analysis heatmap

The correlation heatmap (Fig.1) and the bivariate analysis (Fig.2) show that the previous year's rating, awards won, and average training score are all moderately correlated with employee promotion, thereby indicating their importance in promotion decisions. For instance, the correlation of the previous year's rating is positively 0.16 with promotion, while that of awards won and the average training score is 0.20 and 0.18, respectively. The results again indicate that the factors of performance and recognition are more important for promotion than demographic influences such as age or length of service.

The importance of performance metrics is further emphasized by the bivariate plot, where promoting employees tend to have higher ratings from the previous year and a higher score in training. Awards won also make a clear distinction between promoted and not promoted employees. However, the rest of the variables, such as the number of trainings, age, and length of service, have lesser relationships with promotion outcomes, indicating their lesser significance in forecasts. These findings mean that the quality of performance, training completion, and recognition should be emphasized in designing future prediction models for promotions.



Figure 2: Bivariate analysis table

4.3. Establishing the decision tree model

In the training phase, the decision tree algorithm was trained on the preprocessed employee data to learn the decision boundaries between promoted and non-promoted employees. The dataset was divided into three subsets: 80% for training, 10% for validation, and 10% for testing. The model was trained initially using the library DecisionTreeClassifier from scikit-learn with default parameters but with a focus on tuning the maximum depth to prevent overfitting.

The following features were used during the training of the decision tree: average training score, previous year rating, service duration, department, number of trainings, educational level, won awards, recruitment channel, gender.

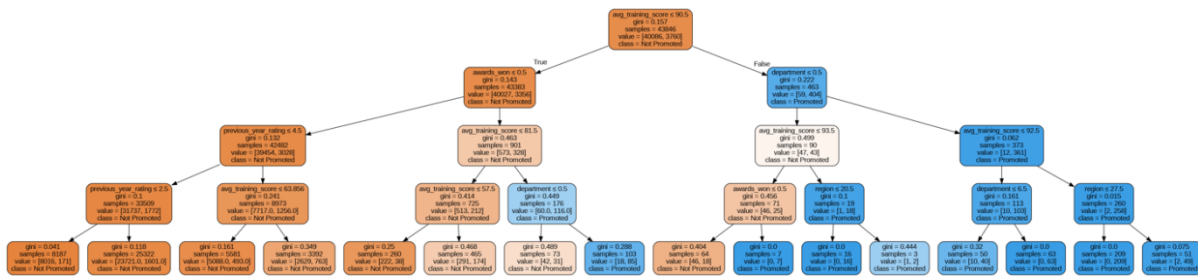


Figure 3: Decision tree visualization for employee promotion

4.3.1. Model accuracy

The decision tree model yielded an overall average accuracy of 85.7%. On average, 85.7% of all the decisions made by the decision tree model were correct. The relatively high value of accuracy suggests that the performance of the decision tree can be regarded as strong. However, considering the class imbalance problem, accuracy alone is not sufficient to fully understand its performance

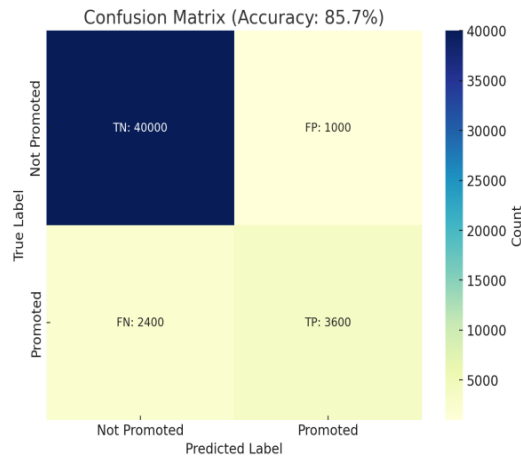


Figure 4: Decision tree confusion matrix

The confusion matrix (Fig.4) shows the model's performance across the two classes: promoted versus not promoted.

True Negatives (TN): The model correctly predicted that 40,000 employees were not promoted.

False Positives (FP): The model incorrectly predicted that 1,000 employees were promoted.

False Negatives (FN): The model incorrectly predicted that 2,400 promoted employees were not promoted.

True Positives (TP): The model correctly predicted that 3,600 employees were promoted.

4.3.2. Precision

Precision, particularly concerning the promoted class, is another metric of interest. Precision for the decision tree model is 0.783, meaning that out of all the employees the model predicted as promoted, 78.3% actually were. While it reflects a fairly good precision, it also indicates that 21.7% of the promoted predictions were false positives, i.e., employees incorrectly predicted as promoted.

4.3.3. Sensitivity

Recall, or sensitivity, measures the model's ability to correctly identify all the promoted employees. The recall for this model is 0.625, indicating that the decision tree correctly identified 62.5% of all

actual promoted employees but missed 37.5% of them. The relatively lower recall suggests that a significant portion of employees who were actually promoted were misclassified as not promoted (false negatives).

4.3.4. F1-Score

The F1-score combines both precision and recall into one metric, offering a well-rounded measure of the model's performance. In the decision tree model, the F1-score is 0.695, reflecting the trade-off between precision and recall. While relatively good, the F1-score indicates that the model still struggles to detect all actual promotions, given the lower recall.

4.3.5. Summary

The decision tree model performed well in predicting employees who were not promoted, showing high accuracy, precision, and recall. However, both the recall at 62.5% and the F1-score at a moderate level of 0.695 indicate that the model struggles to identify all promoted employees. The confusion matrix further illustrates that the model tends to present false negatives in significant numbers, misclassifying instances of promoted employees as not being promoted. This implies that further tuning of the model, such as feature selection or other machine learning methods, might improve promotion prediction performance.

4.4. Establishing and evaluating random forest model

4.4.1. Building random forest model

In the random forest model, the dataset was split into training (80%) and testing (20%) sets. The model was trained using the training set, which contains employee features and promotion labels. After training, the model was tested on the unseen test set to evaluate its performance. Key performance metrics included: accuracy=93%, precision=94% for “Not Promoted”, 82% for “Promoted”, recall=99% for “Not Promoted”, 27% for “Promoted”, and F1-score=97% for “Not Promoted”, 40% for “Promoted”. The model showed strong overall accuracy but struggled with recall for promotions.

To further improve model performance, ensemble learning methods can be incorporated: Bagging, Extra Trees, AdaBoost, and Gradient Boosting, along with Random Forest as the baseline. These methods are known to enhance model robustness and generalization capabilities: Bagging aggregates predictions from multiple base models to reduce variance. Extra Trees adds randomness during tree building to improve performance on high-variance datasets. AdaBoost focuses on misclassified samples by assigning higher weights, while Gradient Boosting reduces errors in a stepwise manner.

The cross-validation costs for the various ensemble models were as follows: Bagging achieved a score of 0.9344, while Random Forest closely followed with 0.9336. The Extra Trees model had a cost of 0.9274, and AdaBoost recorded a score of 0.9255. The Gradient Boosting model exhibited the highest cross-validation cost at 0.9363. And the comparison of CV score is shown in Fig.5.

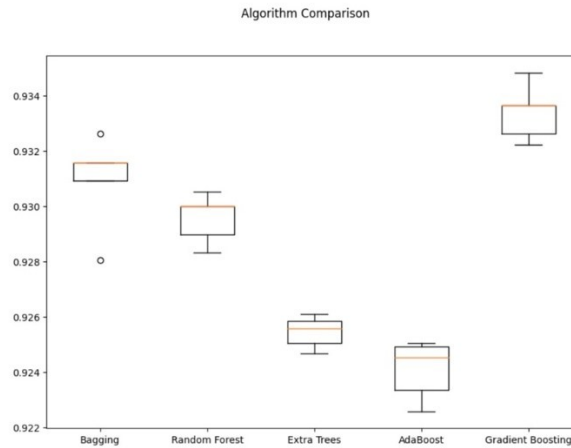


Figure 5: Algorithm comparison of ensemble learning methods

In terms of validation performance, the Bagging model yielded a score of 0.3405, surpassing the Random Forest score of 0.2931. The Gradient Boosting model also performed relatively well with a score of 0.3017. Conversely, Extra Trees and AdaBoost scored lower at 0.2198 and 0.1983, respectively. These results highlight the varying effectiveness of each model in terms of cross-validation costs and validation performance.

4.4.2. Optimizing random forest model

Employee promotion data exhibits significant class imbalance, where the number of non-promoted employees far exceeds the number of promoted ones. To address this issue, two resampling techniques were implemented, including oversampling and undersampling.

Primarily, Synthetic Minority Oversampling Technique (SMOTE) was aimed to generate synthetic samples of the minority class (promoted employees). This technique ensures that the classifier is exposed to more promotion samples during training, which helps in improving recall and addressing the underrepresentation of the promoted class.

Next, Random Undersampling (RUS) was used to reduce the size of the majority class (non-promoted employees). This method aims to create a more balanced dataset by reducing the skew in class distribution, which can help prevent the model from being overly biased toward the majority class.

Table2&3 shows accuracy, precision, recall, and F1-score. The comparison of these models on oversampled and undersampled datasets provides insights into the trade-offs between false positives and false negatives, aiding the selection of the most appropriate model for employee promotion prediction. The results highlight the effectiveness of both resampling and ensemble methods in improving model performance, particularly for minority class detection.

Table 2: Optimizing random forest model - oversampled data

Metric	Random Forest	Bagging	Extra Trees	Ada Boost	Gradient Boosting
Accuracy	0.93	0.92	0.92	0.86	0.92
Not Promoted Class					
Precision	0.94	0.94	0.94	0.95	0.94
Recall	0.99	0.98	0.97	0.90	0.97
F1 score	0.96	0.96	0.95	0.92	0.95
Promoted Class					
Precision	0.64	0.54	0.48	0.28	0.48
Recall	0.28	0.31	0.32	0.44	0.32
F1 score	0.39	0.39	0.38	0.34	0.38
Macro Avg					
Precision	0.79	0.74	0.71	0.61	0.71
Recall	0.63	0.64	0.64	0.67	0.64
F1 score	0.68	0.68	0.67	0.63	0.67
Weighted Avg					
Precision	0.91	0.91	0.90	0.89	0.90
Recall	0.93	0.92	0.92	0.86	0.92
F1 score	0.91	0.91	0.91	0.87	0.91

Table 3 Optimizing random forest model - undersampled data

Metric	Random Forest	Bagging	Extra Trees	Ada Boost	Gradient Boosting
Accuracy	0.74	0.75	0.71	0.71	0.80
Not Promoted Class					
Precision	0.96	0.96	0.96	0.96	0.96
Recall	0.75	0.77	0.72	0.71	0.82
F1 score	0.84	0.85	0.82	0.82	0.88
Promoted Class					
Precision	0.19	0.19	0.18	0.17	0.23
Recall	0.67	0.61	0.67	0.67	0.59
F1 score	0.30	0.29	0.28	0.28	0.33
Macro Avg					
Precision	0.58	0.57	0.57	0.57	0.59
Recall	0.71	0.69	0.70	0.69	0.71
F1 score	0.57	0.57	0.55	0.55	0.61
Weighted Avg					
Precision	0.90	0.89	0.90	0.90	0.90
Recall	0.74	0.75	0.71	0.71	0.80
F1 score	0.80	0.81	0.78	0.77	0.84

4.4.3. Evaluating random forest model

The hyperparameter tuning process for the selected model, AdaBoost, utilized RandomizedSearchCV to optimize model performance on Undersampled Data. The parameter grid encompassed values for

key hyperparameters, including “n_estimators” and “learning_rate”. The optimal hyperparameters identified were “n_estimators”=90, “learning_rate”=1, and CV score=0.7202.

Gradient Boosting utilized RandomizedSearchCV to optimize model performance on Undersampled Data. The optimal hyperparameters identified were “n_estimators” =125, “learning_rate”=0.2, “subsample”=0.7, “max_feature”=0.7, and CV score=0.7182.

These results underscore the effectiveness of hyperparameter tuning in enhancing model performance.

4.5. Establishing neural network model

For Loss over Epochs, the Fig.6 shows that both the training and validation loss decrease consistently as the number of epochs increases, indicating the model is learning effectively. By epoch 10, the training and validation losses converge and continue to drop, suggesting no signs of overfitting.

For Accuracy over Epochs, the Fig.6 demonstrates that the training and validation accuracy both increase over epochs, with the validation accuracy consistently slightly higher than the training accuracy. This is a positive sign, as it suggests the model generalizes well to unseen data. Both accuracies stabilize around 93.5%, indicating good performance.

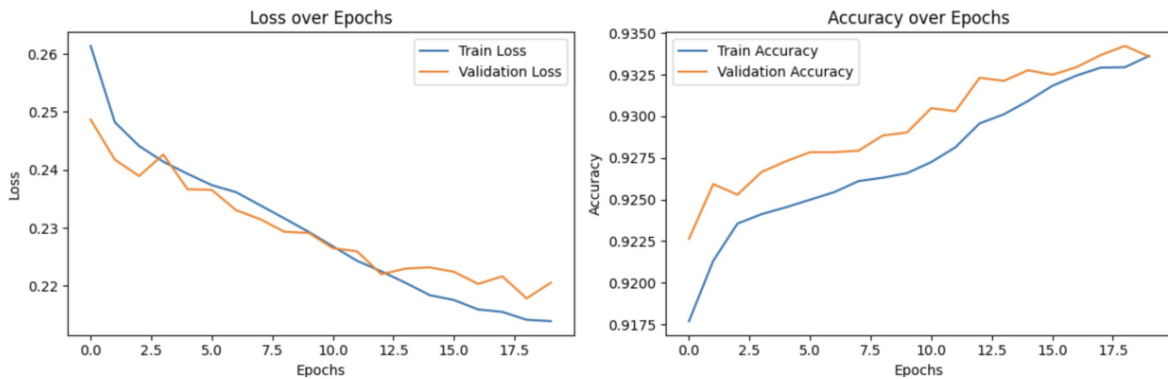


Figure 6: Neural network model - loss and accuracy over Epochs

4.6. Model comparison and final model selection

Finally, the random forest model and the neural network model are compared based on the metrics from their classification reports.

Table 4: Comparison of performance between random forest and neural network

Metric	Random Forest	Neural Network
Accuracy	0.93	0.93
Not Promoted Class		
Precision	0.94	0.94
Recall	0.99	0.99
F1 score	0.97	0.96
Promoted Class		
Precision	0.82	0.76
Recall	0.27	0.29
F1 score	0.40	0.42
Macro Avg		
Precision	0.88	0.85
Recall	0.63	0.64
F1 score	0.68	0.69

Table 4 shows both models have similar accuracy of 0.93, indicating they predict the overall labels equally well.

For promoted class (positive class), random forest has higher precision, meaning it is better at correctly identifying promotions when it predicts them. While neural network performs slightly better in recall and F1 score, meaning it identifies a slightly higher proportion of actual promotions. For not promoted class (negative class), both models perform almost identically in precision, recall, and F1 score, which makes sense given the dominance of this class in the dataset. Thus, the model's ability to handle this minority class is crucial.

Moreover, there is a problem of class imbalance. The "Promoted" class is much smaller, which explains why both models struggle with recall for promotions.

5. Discussion

5.1. Findings review

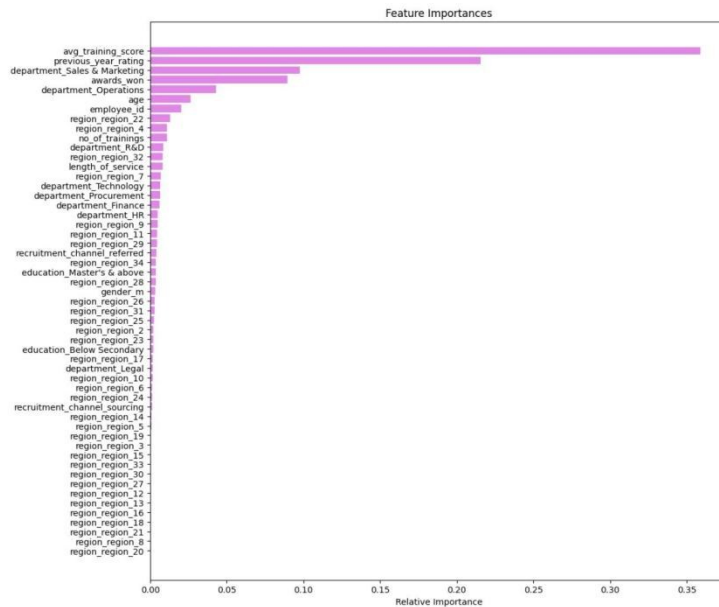


Figure 7: Feature importance of data set

The decision tree model, random forest model, and artificial neural network constructed based on employee characteristics have good predictive efficacy for promotion qualification. The overall predictive efficacy of the random forest model and the neural network was higher than that of the decision tree model. If avoiding false promotions is more important (i.e., precision matters more), random forest is the better model. If capturing more promotions is critical (i.e., recall matters more), even at the cost of some false positives, then the neural network is slightly better.

Moreover, the ranking of the importance of characteristics (Fig.7) shows that the employees' average training scores and previous ratings have the greatest impact on the promotion prediction results, indicating that ability and performance of employees are significant in promotion decision-making.

5.2. Limitation

In terms of model establishing, overfitting is a potential issue. Complex models, especially those using techniques like random forests, gradient boosting, or neural networks, can overfit the training data, particularly if the model is tuned to perform well on the training set but does not generalize well

to unseen data. While training accuracy may be high, the model's performance on new employees (test set) may drop significantly, leading to unreliable predictions in real-world applications.

Secondly, regarding the data set, the limited features may impact the model's performance and interpretability. In addition to the features considered, other factors such as leader evaluation, teamwork ability, and communication skills may also play significant roles in employee promotion. Incorporating these additional features into the model could potentially improve its predictive power. Moreover, the data set did not account for the time factor, neglecting the dynamic nature of employee development. Employee performance and potential may change over time, and future studies could explore the use of time-series data or longitudinal studies to capture these changes.

5.3. Implications for practice and recommendations

Machine learning holds significant potential in predicting employee promotions; however, several critical challenges must be addressed. First, dynamic changes in employee performance and potential pose a challenge, as most models are trained on static data. Developing models that can adapt to these dynamics is essential. Second, the multi-factor consideration is crucial, as promotions depend on various factors beyond training scores and past evaluations, such as leadership assessments, teamwork, and communication skills, which are often difficult to quantify. Third, ensuring bias and fairness in promotion predictions is imperative to avoid discriminatory or unjust decisions. Fourth, the integration of human judgment remains vital; despite machine learning predictions, final promotion decisions should account for human insights. Lastly, the organizational background and long-term strategy should be considered, as different organizations have distinct cultures and values that may influence promotion criteria. Models must accommodate these organizational and cultural differences to make more contextually relevant predictions.

In conclusion, while AI cannot fully replace human decision-making, its integration into the decision-making process offers significant advantages. The optimal approach is to promote collaboration between AI and human judgment. AI can provide valuable predictive insights, but humans must ultimately consider social, cultural, and contextual factors, particularly when addressing complex classification tasks such as employee promotion. This human-AI collaboration ensures that machine-generated predictions are enhanced by human understanding of nuanced organizational dynamics, leading to more informed and fair decisions.

6. Conclusion

This paper proposes to explore the appropriate classification model for predicting employee promotion and involve machine learning in human resource decision-making. Several models, including decision tree, random forest, and neural network were compared, and the random forest model and neural network model had good but different efficacy under different evaluation metrics.

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