Predictive Modeling for Salary Categorization of Employees

Introduction

Organizations face the ongoing problem of successfully managing and compensating their employees in today's dynamic and continually evolving workforce. Employee remuneration affects not only a person's financial stability, but also their job satisfaction, motivation, and overall performance. However, effectively categorizing employee pay as high, medium, or low is a difficult undertaking that necessitates a thorough grasp of the different elements that influence compensation decisions. As a result, organizations frequently struggle to maintain a fair and transparent remuneration system that is aligned with employee contributions.

The significance of resolving this issue cannot be emphasized. Employee engagement, retention, and productivity are all dependent on a fair and balanced compensation scheme. When employees believe their compensation are consistent with their talents, expertise, and efforts, it generates a sense of justice and motivates them to achieve to their full potential. An unfair or misaligned remuneration structure, on the other hand, can lead to demotivation, decreased job satisfaction, and increased turnover rates, hurting organizational performance.

To solve this essential issue, this research proposes developing predictive models capable of accurately categorizing employee pay based on a wide range of independent parameters. We hope to capture the multifaceted nature of salary categorization by utilizing a variety of variables such as the individual's level of happiness, average monthly working hours, tenure within the organization, current employment status, past promotions within the last five years, and department affiliation (particularly the sales department).

This study will use four distinct types of predictive models—logistic regression, random forests, decision trees, and naive Bayes—to see which strategy is most effective for properly forecasting employee compensation categories. We will choose the best-performing model based on scoring measures like as accuracy, precision, F1 score, and recall score.

The data set chosen for this project is the "HR_comma_sep", (https://www.kaggle.com/datasets/liujiaqi/hr-comma-sepcsv) from Kaggle. This data set contains 14998 records of employees and 10 variables/features.

Analysis and Insights EDA

To analyze the dataset, EDA employs a number of approaches and tools, such as summary statistics, data visualization, and data cleaning.

a) Descriptive statistics

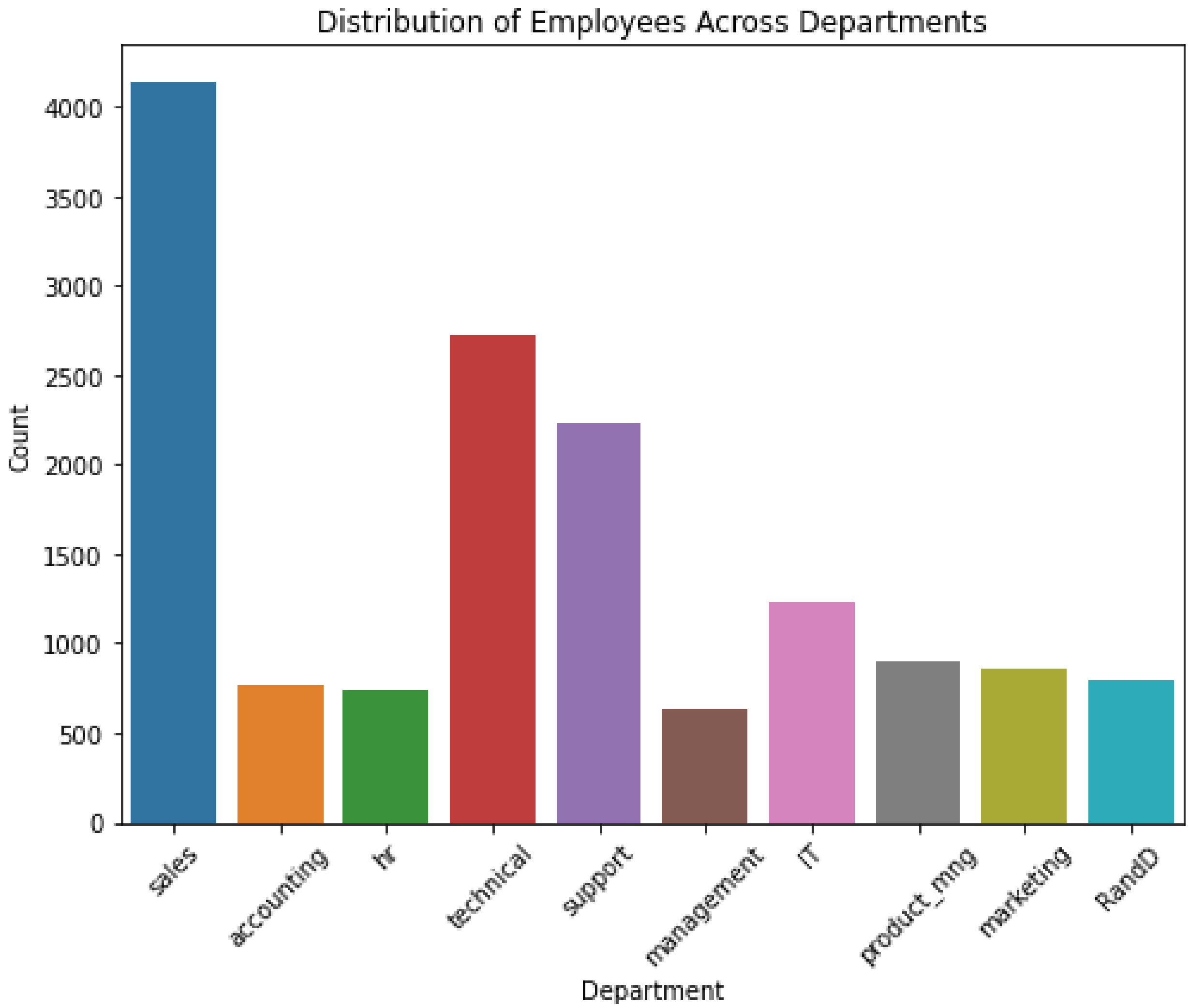
```
df.describe()
```

	satisfaction_level	last_evaluation	number_project	average_montly_hours	time_spend_company	Work_accident	left	promotion_last_5years
count	14999.000000	14999.000000	14999.000000	14999.000000	14999.000000	14999.000000	14999.000000	14999.000000
mean	0.612834	0.716102	3.803054	201.050337	3.498233	0.144610	0.238083	0.021268
std	0.248631	0.171169	1.232592	49.943099	1.460136	0.351719	0.425924	0.144281
min	0.090000	0.360000	2.000000	96.000000	2.000000	0.000000	0.000000	0.000000
25%	0.440000	0.560000	3.000000	156.000000	3.000000	0.000000	0.000000	0.000000
50%	0.640000	0.720000	4.000000	200.000000	3.000000	0.000000	0.000000	0.000000
75%	0.820000	0.870000	5.000000	245.000000	4.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	7.000000	310.000000	10.000000	1.000000	1.000000	1.000000

The table above provides the summary of descriptive statistics which includes the mean, standard deviation, minimum and maximum of all the variables.

b)

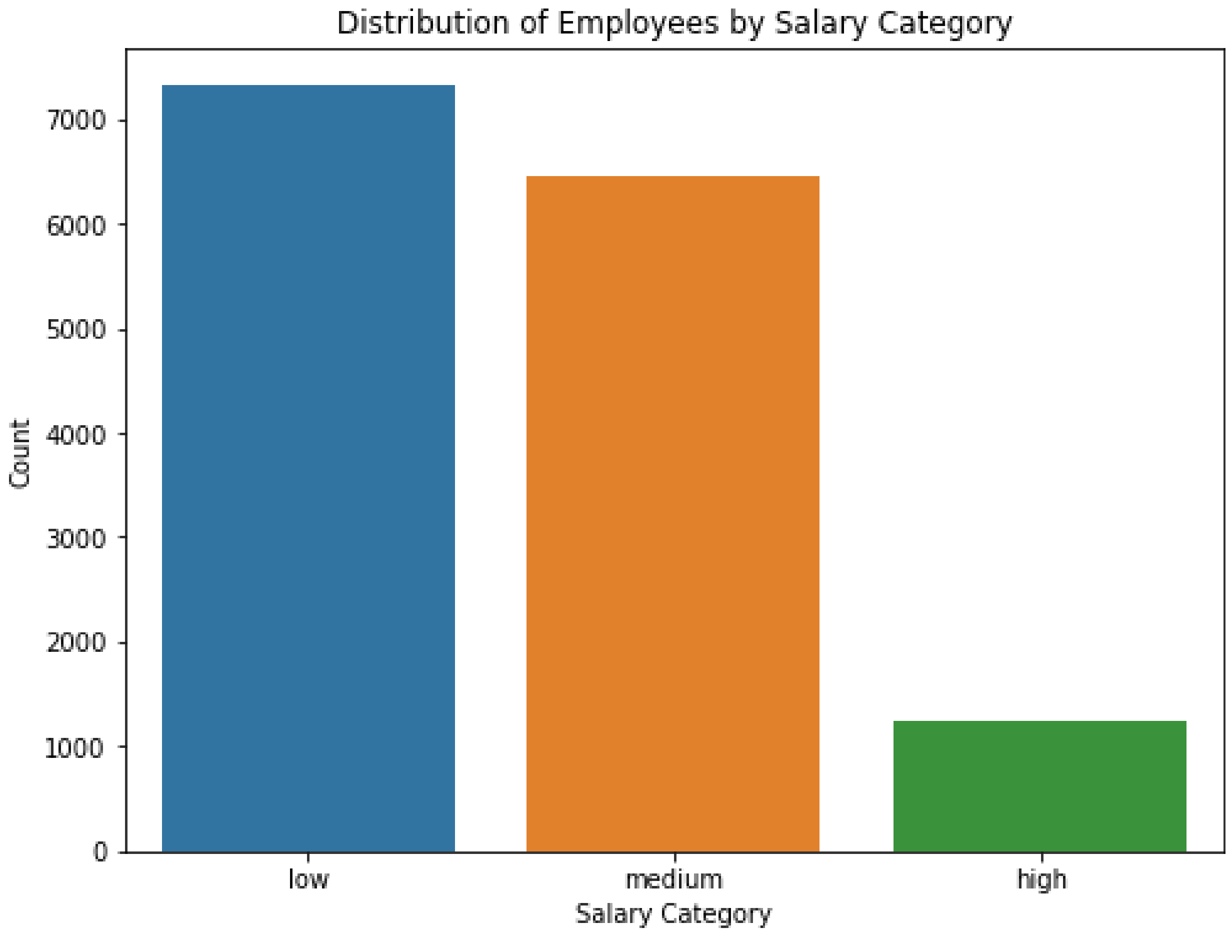
Distribution of Department



The distribution shows that the sales department has the highest distribution of employees while management department has the least number of employees.

c)

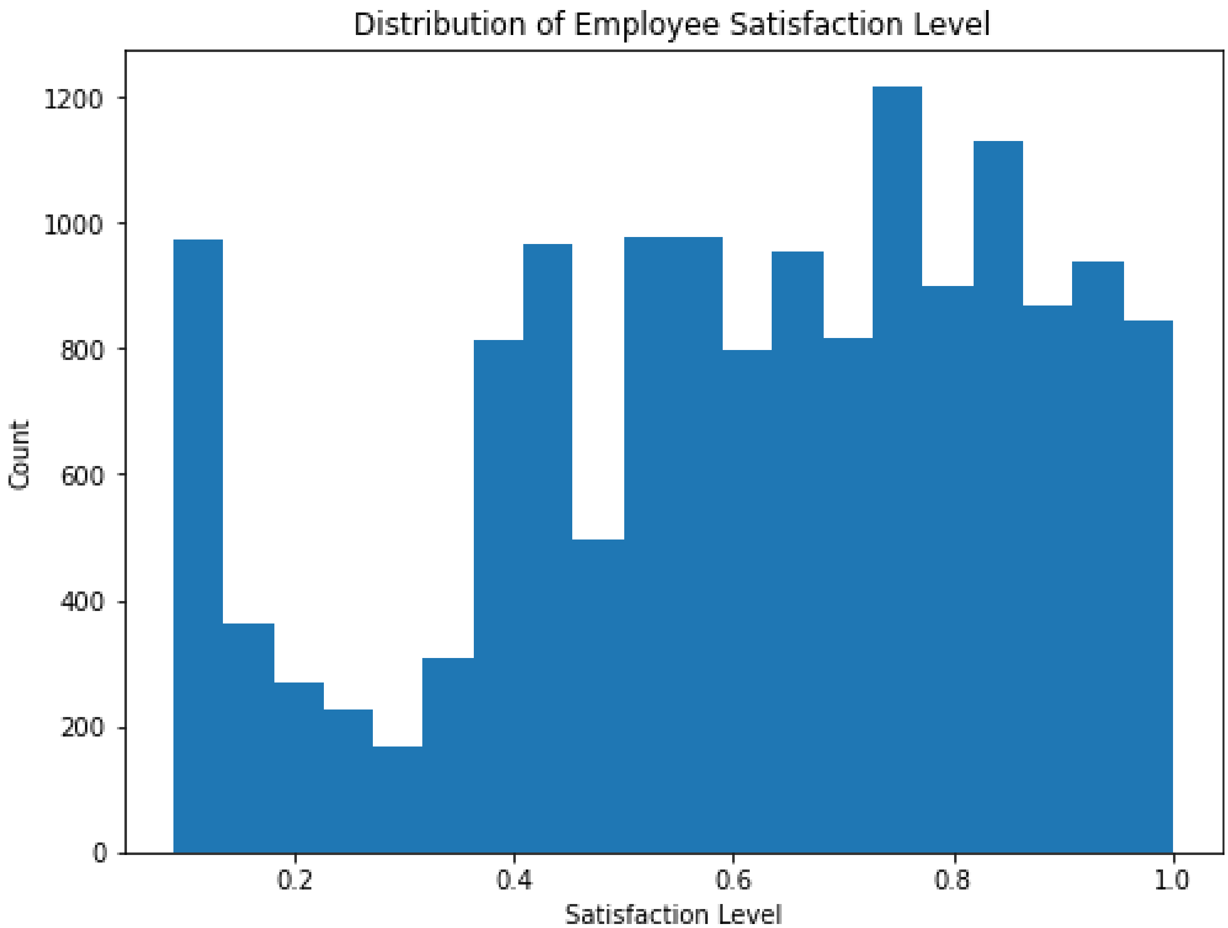
Distribution of sales Category



The distribution shows that the number of employees who receive low salary is higher followed by medium category while high salaried employees are the least.

d)

Distribution of satisfaction level



The distribution of satisfaction level is not normally distributed i.e. its not symmetric.

Data Preparation

The data preparation phase is a crucial step in research, ensuring that the dataset is cleaned, transformed, and organized for further analysis and modeling. The data preparation techniques performed on this data include Feature Scaling, One-Hot Encoding, Binning, Log Transformation and Feature Interaction.

e)

Model Building

The model development phase is an important element in this research since it involves developing prediction models to appropriately categorize employee compensation as high, medium, or low based on a range of independent characteristics. During this step, relevant modelling approaches are chosen, models are trained on the prepared dataset, their performance is evaluated, and the best-performing model is chosen for further research. For this research, 4 types of models are used to predict salary i.e. logistics regression, random forests, decision trees and naive Bayes and use scoring metrics that includes accuracy, precision, F1 score and recall score to determine the best model for predicting employee's salary.

```
Logistic Regression:
Confusion Matrix:
[[   0  144  109]
 [   0 1063  411]
 [   0  849  424]]
Accuracy: 0.49566666666666664
Precision: 0.44462119963068003
Recall: 0.49566666666666664
F1 Score: 0.45822052480553094

Random Forest:
Confusion Matrix:
[[  83   89   81]
 [   6 1036  432]
 [  11  506  756]]
Accuracy: 0.625
Precision: 0.6348825522783307
Recall: 0.625
F1 Score: 0.619926740595221

Decision Trees:
Confusion Matrix:
[[ 95  80  78]
 [ 88 947 439]
 [ 85 441 747]]
Accuracy: 0.5963333333333334
Precision: 0.5976240790473013
Recall: 0.5963333333333334
F1 Score: 0.5969487315855411
```

```
Naive Bayes:
Confusion Matrix:
[[  18  210   25]
 [  27 1339  108]
 [  51 1103  119]]
Accuracy: 0.492
Precision: 0.4642672930283225
Recall: 0.492
F1 Score: 0.3938252114579391
```

From the model development and evaluation, the following conclusions can be drawn:

1. Logistic Regression: The accuracy of the logistic regression model was approximately 49.6%. Additionally, the precision, recall, and F1 score were relatively low.
2. Random Forest: The random forest model outperformed logistic regression by approximately 62.5% in terms of accuracy. As indicated by the confusion matrix, its performance improved across all salary brackets. In comparison to logistic regression, the precision, recall, and F1 score were notably higher.
3. Decision Trees: The accuracy of the decision tree model was approximately 59.6%. The performance was comparable to that of random forest, albeit with slightly inferior precision, recall, and F1 score values. However, it was still superior to logistic regression.
4. The accuracy of the naive Bayes model was approximately 49.2 percent. Additionally, the precision, recall, and F1 score were relatively low.

Overall, among the evaluated models, the random forest model demonstrated the highest levels of accuracy, precision, recall, and F1 score. Compared to other models, it demonstrated a superior ability to predict differences in salary categories.

Conclusion

Based on the results of the model development and evaluation, several conclusions can be drawn. The random forest model emerged as the most promising among the evaluated models. It showcased the highest levels of accuracy, precision, recall, and F1 score, indicating its superior ability to predict salary categories. Therefore, it could be considered for deployment in practical applications.

However, before deploying the model, several considerations and challenges need to be explored. First, it is important to assess the generalizability of the model on unseen data to ensure its robustness. Additionally, further analysis should be conducted to understand the factors that contribute most to the model's predictions, as this can provide valuable insights and enhance interpretability.

Moreover, the performance of the model should be evaluated on diverse datasets to account for potential biases and ensure fair predictions across different demographic groups. It is crucial to address any biases present in the data or the model itself to avoid perpetuating discriminatory outcomes. Furthermore, ongoing monitoring and re-evaluation of the deployed model's performance is essential to detect any degradation in accuracy or biases that may arise due to evolving data patterns or changes in the target population.

In conclusion, while the random forest model demonstrates promising performance, additional exploration and validation are necessary before deploying it in real-world applications. Addressing potential challenges such as generalizability, interpretability, bias mitigation, and ongoing monitoring will contribute to the model's readiness and reliability.