

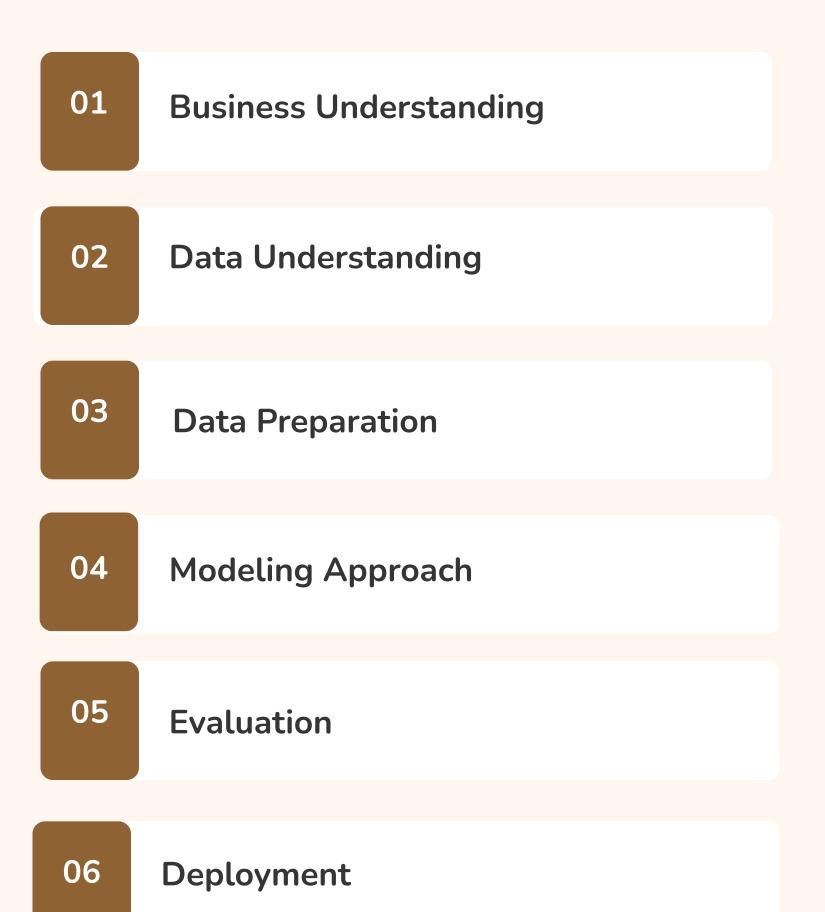
Predicting Employee Resignations to Enhance Retention and Productivity

Machine Learning for Workforce Optimization

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Business

Understanding Business Problem:

High employee resignation rates are impacting organizational productivity and increasing costs due to frequent hiring and training.

Goal:

Predict employee resignations and identify key factors influencing them.

Propose actionable strategies to enhance retention and productivity.

Value:

Help HR teams make data-driven decisions to reduce employee turnover.

Data Understanding

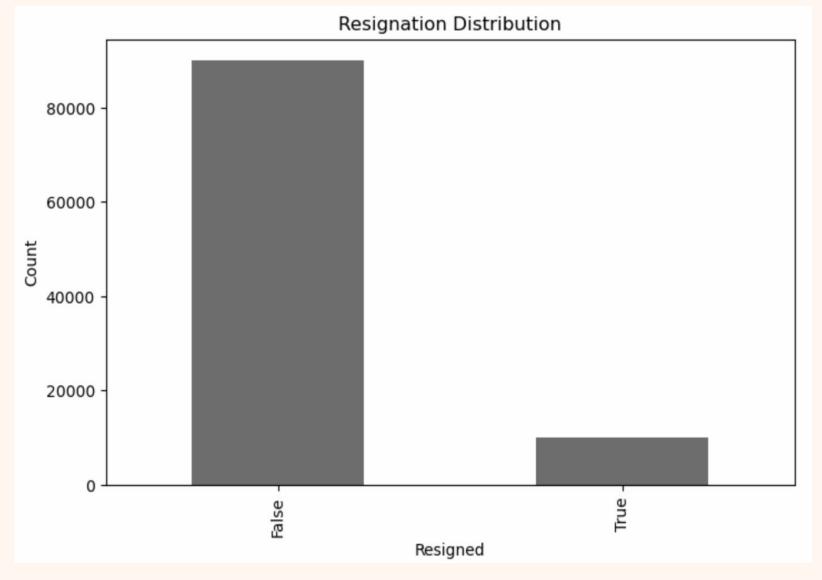
Dataset Overview

Source: <u>Kaggle - Employee Performance</u> and Productivity Data.

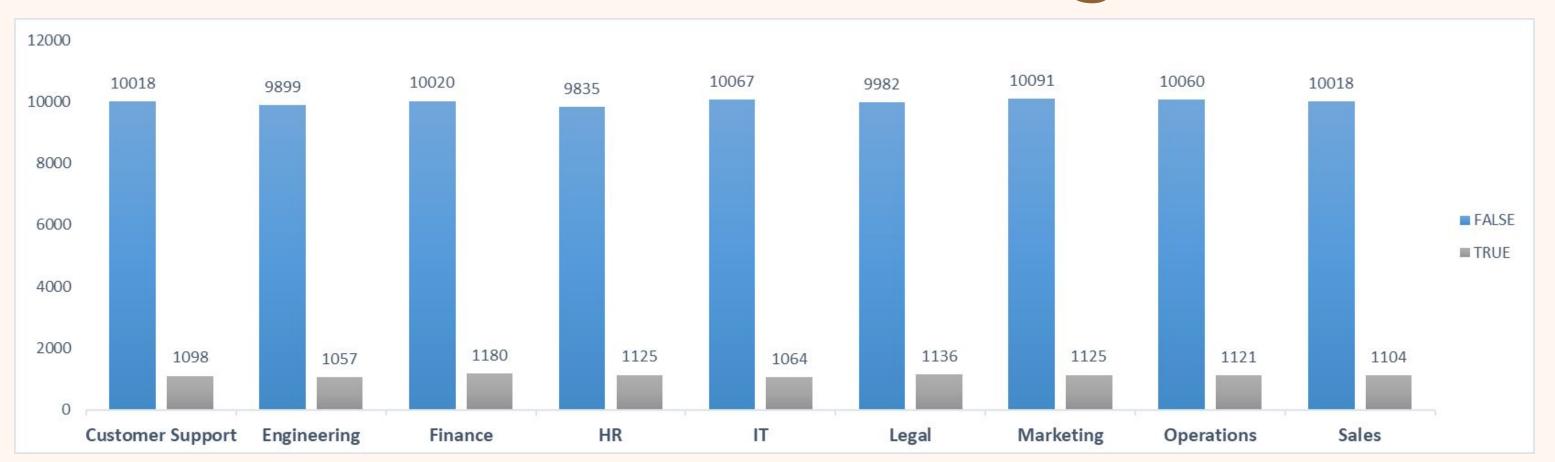
Data after handling datetime columns: <class 'pandas.core.frame.DataFrame'> RangeIndex: 100000 entries, 0 to 99999 Data columns (total 22 columns): Column Non-Null Count Dtype Employee ID 100000 non-null int64 Department 100000 non-null object Gender 100000 non-null object Age 100000 non-null int64 Job_Title 100000 non-null object Years At Company 100000 non-null int64 Education_Level 100000 non-null object Performance_Score 100000 non-null int64 Monthly_Salary 100000 non-null int64 Work_Hours_Per_Week 100000 non-null int64 Projects Handled 100000 non-null int64 Overtime_Hours 100000 non-null int64 Sick_Days 100000 non-null int64 Remote_Work_Frequency 100000 non-null int64 14 Team_Size 100000 non-null int64 Training_Hours 100000 non-null int64 Promotions 100000 non-null int64 Employee_Satisfaction_Score 100000 non-null float64 18 Resigned 100000 non-null bool Hire_Date_year 100000 non-null int32 20 Hire_Date_month 100000 non-null int32 21 Hire_Date_day 100000 non-null int32 dtypes: bool(1), float64(1), int32(3), int64(13), object(4) memory usage: 15.0+ MB None



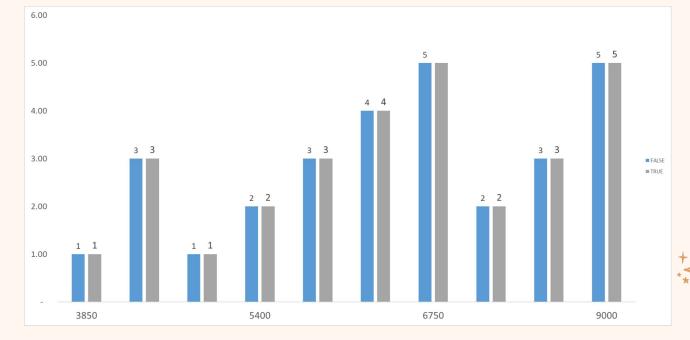
Target Variable: Resignation Status (True/False).



Data Understanding









Profit Matrix



True Positive

Correctly predicting resignation and intervening.

• Cost: \$10,000

• Benefit: \$50,000

• Net Savings: \$40,000

False Negative

Failing to predict an employee is going to resign.

• Cost: \$50,000

• Net Loss: \$50,000

False Positive

Predicting an employee will resign when they were not going to.

• Cost: \$10,000

• Net Loss: \$10,000

True Negative

Correctly predicting an employee will stay

Net Savings of 0

Example Scenario Assumptions

Employee Count: 1,000 employees

Annual Turnover Rate: 15% (150 resignations per year)

Average Turnover Cost per Employee: \$50,000 (includes recruiting, training, lost productivity, etc.)

Retention Intervention Cost: \$10,000 per employee (e.g., salary adjustment, training, incentives).

Model Accuracy Assumptions:

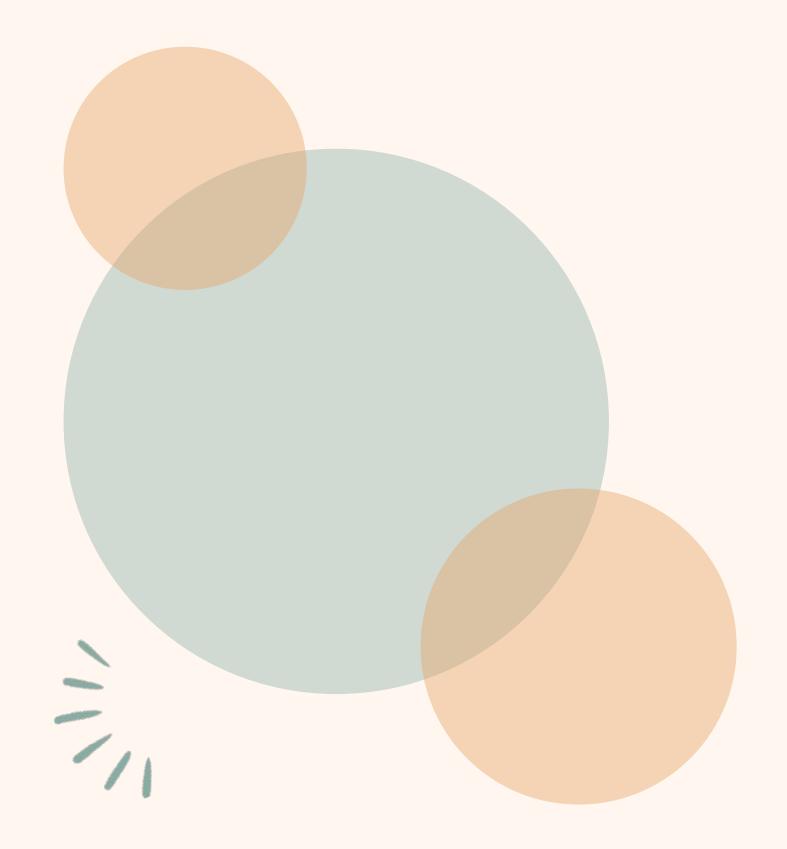
True Positive Rate (Recall): 80%
True Negative Rate (Specificity): 90%

False Positive Rate: 10% False Negative Rate: 20%

Overall Cost-Benefit Calculation

True Positives (120 employees): Savings = 120 × \$40,000 = \$4,800,000.	False Positives (100 employees): Cost = 100 × \$10,000 = \$1,000,000.
True Negatives (850 employees): Savings = $850 \times $0 = 0 .	False Negatives (30 employees): Cost = 30 × \$50,000 = \$1,500,000.





Net Savings & Insights

Total Savings = \$4,800,000Total Costs = \$1,000,000 + \$1,500,000 = \$2,500,000

Net Savings = \$2,300,000

<u>Insights</u>

True Positives drive the majority of the savings by avoiding turnover costs

False Positives are less expensive than False Negatives, as retention efforts are cheaper than turnover costs.

Improving the recall is key to maximizing savings

Data Preparation

STEPS TAKEN

1. EncodingCategoricalVariables

2. HandlingMissingValues

3. Scaling
Numerical
Features

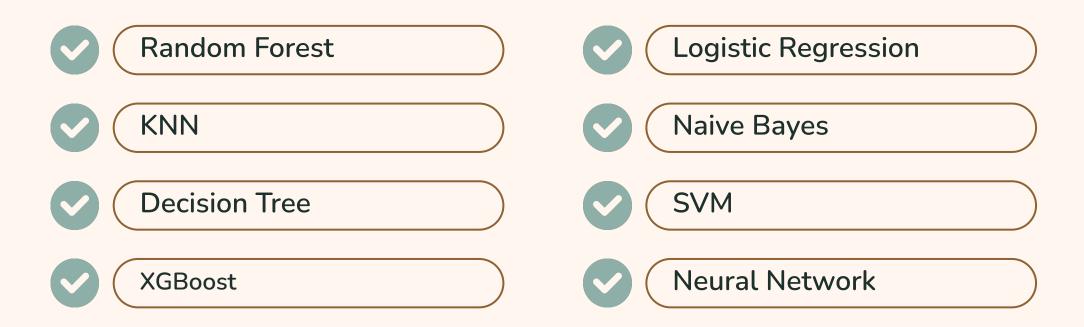
4. Outlier
Detection and
Removal

Split our dataset of 100,000 entries into 70% training and 30% testing data



Modeling Approach

We experimented the following Classification models:



We followed these steps:

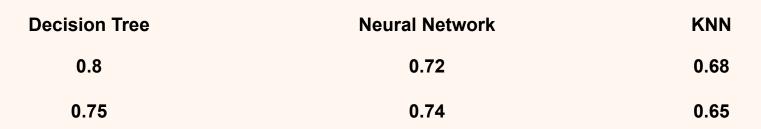
- 1. Initial Modeling: Built and evaluated 8 models.
- 2. **Best Model Selection:** Chose the top-performing model based on their performance.
- 3. **SMOTE Analysis:** Applied SMOTE to address class imbalance and refine model performance, again choosing a best model.
- 4. Hyperparameter Tuning: Optimized the top 2-3 models for the best performance.



Model Selection

Recall

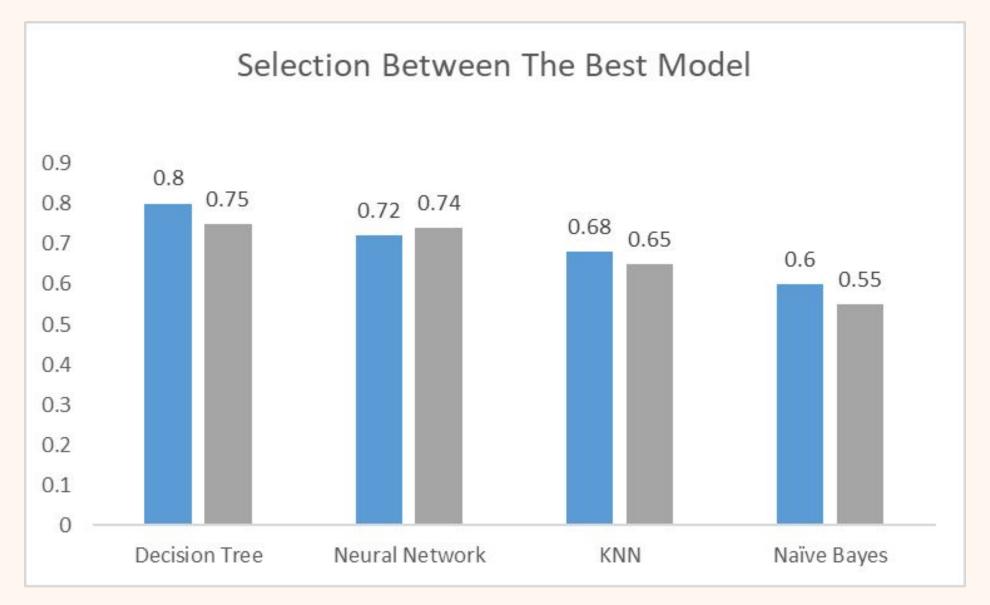
F1



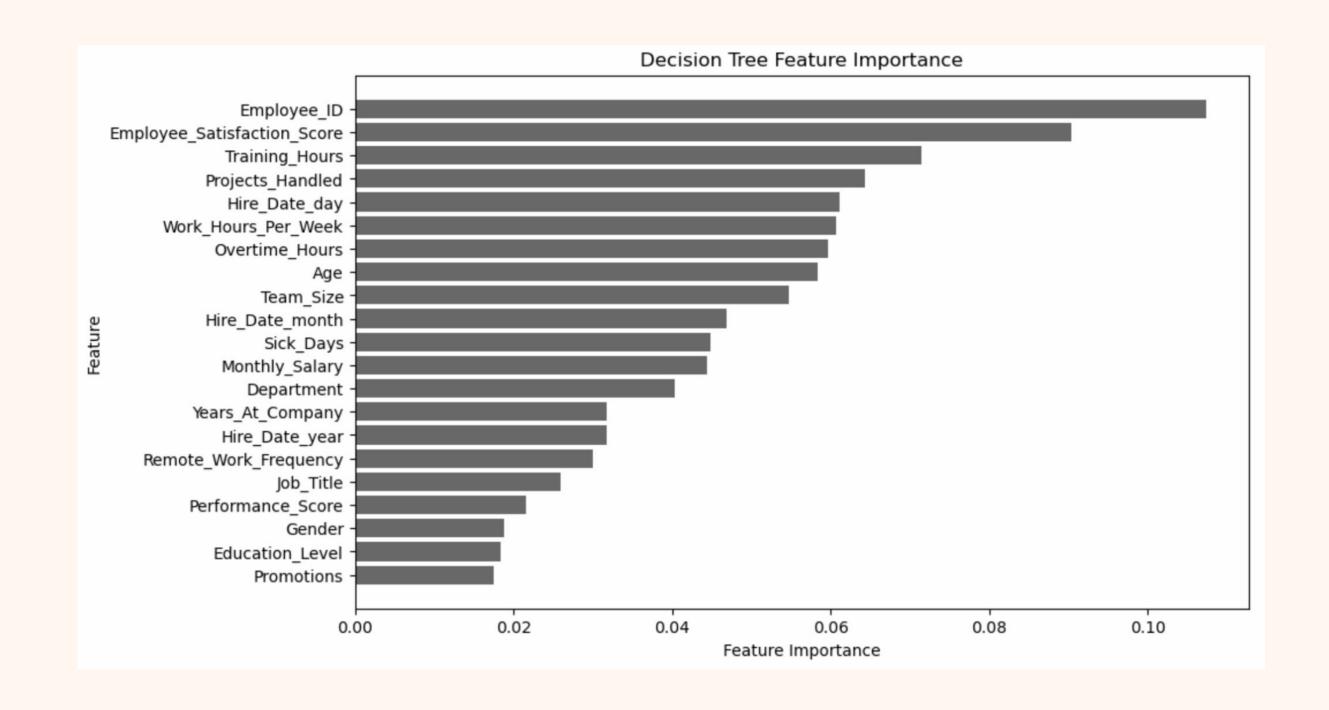
Naïve Bayes

0.6

0.55



Evaluation



Deployment

- The best Decision Tree model was saved as best_decision_tree_model.pkl using joblib to enable seamless reuse and deployment.
- This ensures quick integration into HR systems for real-time resignation predictions, saving time and computational resources.

New Sample Data				
Employee_ID	1001	1002	1003	
Department	Sales	IT	HR	
Gender	Male	Female	Female	
Age	30	25	40	
Job_Title	ales Executiv	Software Engineer	IR Manager	
Hire_Date	2020-01-15	2019-06-10	2018-09-20	
Years_At_Company	4	5	6	
Education_Level	Bachelor	Master	Bachelor	
Performance_Score	3	4	2	
Monthly_Salary	5000	7000	6500	
Work_Hours_Per_Week	40	45	35	
Projects_Handled	3	5	2	
Overtime_Hours	5	10	3	
Sick_Days	2	1	4	
Remote_Work_Frequency	50	80	20	
Team_Size	5	8	4	
Training_Hours	20	15	25	
Promotions	1	2	0	
Employee_Satisfaction_Score	4	5	3	

Predictions for Employees		
1001	0	
1002	1	
1003	1	

0 - not resigned

1 - resigned

Thank You!!

Any Questions?

