Improving Employee Retention by Predicting Employee Attrition Using Machine Learning

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A fresh graduate in Data Science with high interest artificial intelligence, data science, and business analytics. Experienced in data cleaning, exploratory data analysis, visualization, machine learning, and basic deep learning through academic, bootcamps, courses, and personal projects.

Supported by:
Rakamin Academy
Career Acceleration School
www.rakamin.com

Project Overview

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Background

Human resources (HR) are the company's most valuable asset and must be managed effectively to achieve business goals. In this project, we focus on understanding how to retain employees and reduce turnover, which otherwise leads to high recruitment and training costs. By identifying the key factors that drive attrition, the company can design relevant programs to improve employee satisfaction and retention.

Goal

Understand and analyze employee behavior using historical HR data to identify the key factors influencing attrition.

Objective

Develop a predictive model that identifies employees at risk of resigning by leveraging demographic, performance, and engagement data, allowing the company to implement proactive, data-driven HR interventions that reduce turnover and optimize workforce management.

Link to Jupyter Notebook

Dataset Information

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```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 287 entries, 0 to 286
Data columns (total 25 columns):
 #   Column                             Non-Null Count  Dtype  
---  ------                             --------------  -----  
 0   Username                           287 non-null    object 
 1   EnterpriseID                       287 non-null    int64  
 2   StatusPernikahan                   287 non-null    object 
 3   JenisKelamin                       287 non-null    object 
 4   StatusKepegawaian                  287 non-null    object 
 5   Pekerjaan                          287 non-null    object 
 6   JenjangKarir                       287 non-null    object 
 7   PerformancePegawai                 287 non-null    object 
 8   AsalDaerah                         287 non-null    object 
 9   HiringPlatform                     287 non-null    object 
 10  SkorSurveyEngagement               287 non-null    int64  
 11  SkorKepuasanPegawai                282 non-null    float64
 12  JumlahKeikutsertaanProjek          284 non-null    float64
 13  JumlahKeterlambatanSebulanTerakhir 286 non-null    float64
 14  JumlahKetidakhadiran               281 non-null    float64
 15  NomorHP                            287 non-null    object 
 16  Email                              287 non-null    object 
 17  TingkatPendidikan                  287 non-null    object 
 18  PernahBekerja                      287 non-null    object 
 19  IkutProgramLOP                     29 non-null     float64
 20  AlasanResign                       221 non-null    object 
 21  TanggalLahir                       287 non-null    object 
 22  TanggalHiring                      287 non-null    object 
 23  TanggalPenilaianKaryawan           287 non-null    object 
 24  TanggalResign                      287 non-null    object 
dtypes: float64(5), int64(2), object(18)
memory usage: 56.2+ KB
```

The dataset contains **25 columns** and **287 rows**. Several columns, such as Employee Satisfaction Score, Number of Projects Joined, Recent Monthly Lateness, Absenteeism, Participation in the LOP Program, and Resignation Reason, contain missing values. These missing values must be handled before moving forward with eda.

Data Cleaning for EDA

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```
Username                              0
EnterpriseID                          0
StatusPernikahan                      0
JenisKelamin                          0
StatusKepegawaian                     0
Pekerjaan                             0
JenjangKarir                          0
PerformancePegawai                    0
AsalDaerah                            0
HiringPlatform                        0
SkorSurveyEngagement                  0
SkorKepuasanPegawai                   5
JumlahKeikutsertaanProjek             3
JumlahKeterlambatanSebulanTerakhir    1
JumlahKetidakhadiran                  6
NomorHP                               0
Email                                 0
TingkatPendidikan                     0
PernahBekerja                         0
IkutProgramLOP                      258
AlasanResign                         66
TanggalLahir                          0
TanggalHiring                         0
TanggalPenilaianKaryawan              0
TanggalResign                         0
dtype: int64
```

The column *IkutProgramLOP* (Participation in LOP Program) has over 90% missing values and was removed from the dataset. For the AlasanResign column, missing values were imputed with "Unknown." Columns with smaller portions of missing data, such as SkorKepuasanPegawai, JumlahKeikutsertaanProjek, JumlahKeterlambatanSebulanTerakhir, dan JumlahKetidakhadiran, were imputed using statistical measures.

Data Cleaning for EDA

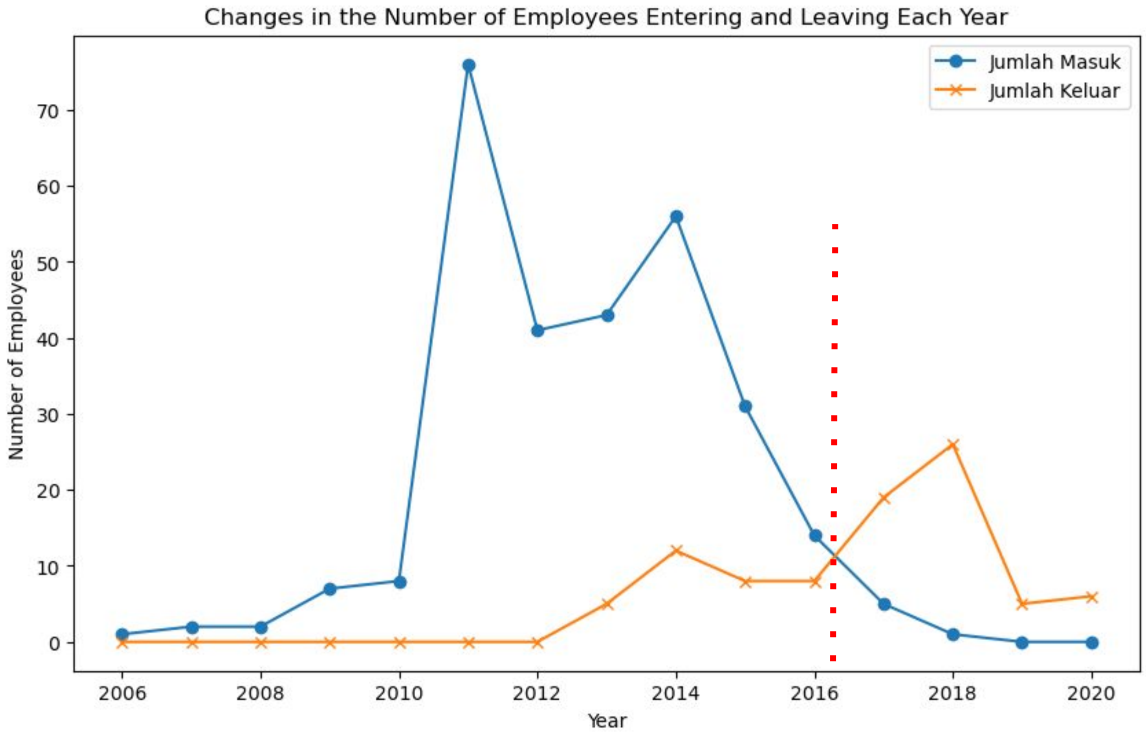

```
Value Counts - PernahBekerja
1        286
yes        1
Name: count, dtype: int64
```

```
Value Counts - StatusPernikahan
Belum_menikah     132
Menikah            57
Lainnya            48
Bercerai           47
-                   3
Name: count, dtype: int64
```

One category in the PernahBekerja column only contained a single value, so the column was removed. Additionally, the “–” category in StatusPernikahan was merged with Lainnya since both categories carry similar meaning.

Exploratory Data Analysis

2017 Was a Turning Point for Employee Retention



Between 2006 and 2016, the company consistently experienced positive growth in employee numbers, as new hires always exceeded resignations. However, **2017 marked a turning point**: the number of resignations began to surpass new hires.

Exploratory Data Analysis

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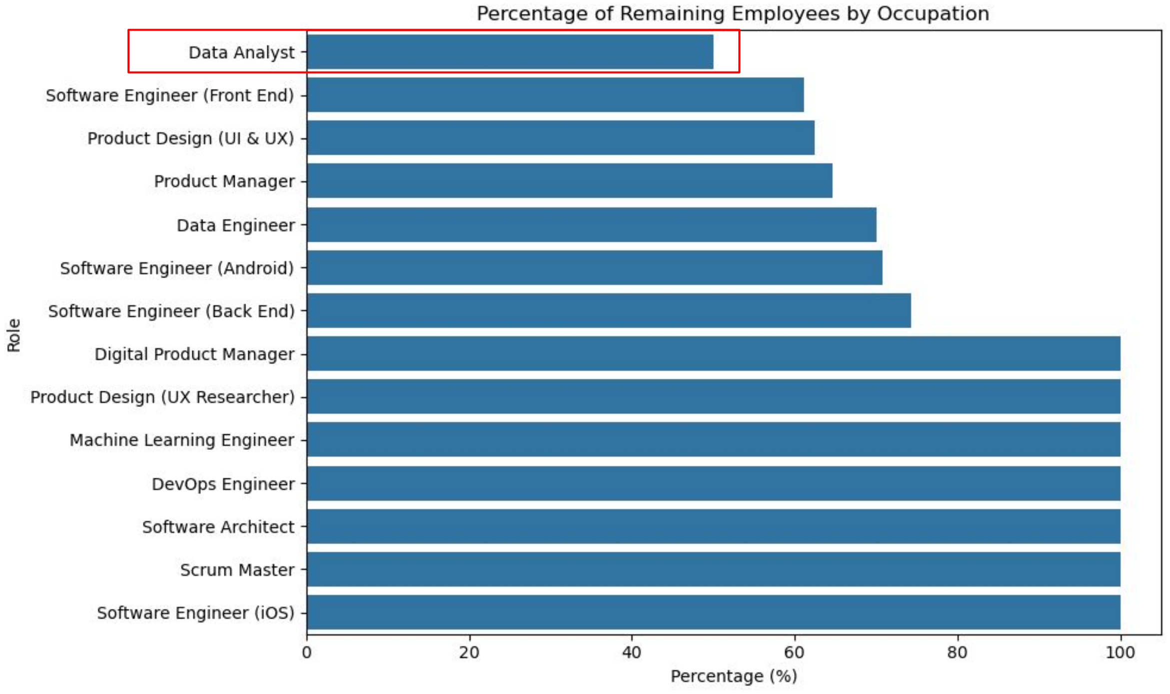
50% of Data Analyst Employees Resign



The ***Data Analyst*** role has the highest resignation rate, with **50% of employees leaving**, followed by other strategic positions such as *Front End Engineer* (40%) and *UI/UX Designer* (37.5%). High attrition in these technical roles signals serious retention challenges, risking project continuity and increasing the workload for remaining staff.

Exploratory Data Analysis

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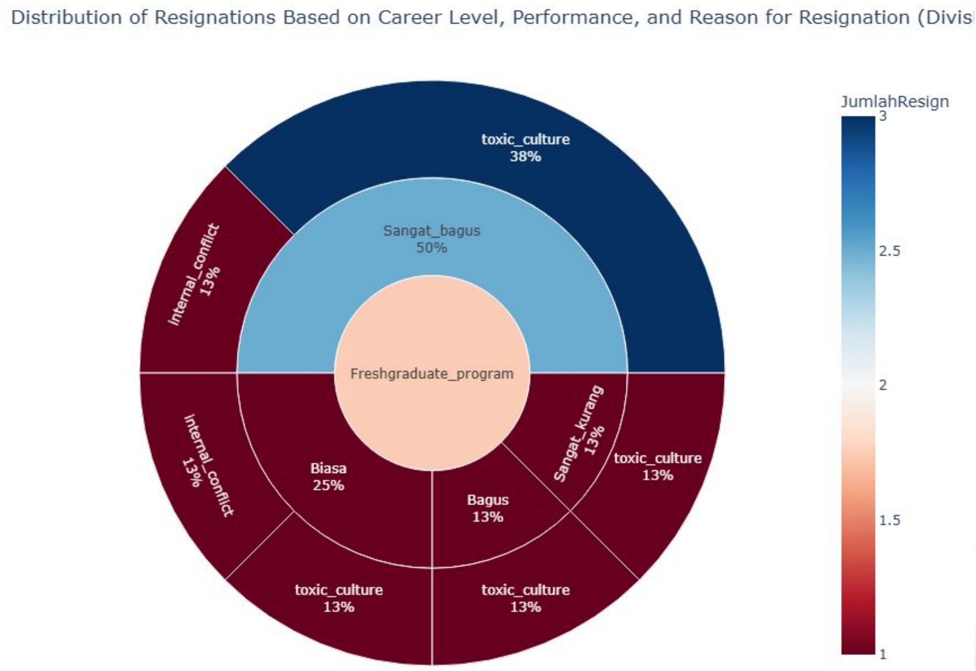
Toxic Culture is the Main Reason Top Talent Resigns



A large proportion of employees who resigned actually came from **high-performance groups**. The leading cause is ***toxic work culture* (38%)**, followed by ***internal conflict* (13%)**. Toxic culture appears consistently across most categories, making it the primary driver of attrition among top talent.

Data Cleaning for Modeling

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 287 entries, 0 to 286
Data columns (total 18 columns):
 #   Column                             Non-Null Count  Dtype  
---  ------                             --------------  -----  
 0   StatusPernikahan                   287 non-null    object 
 1   JenisKelamin                       287 non-null    object 
 2   StatusKepegawaian                  287 non-null    object 
 3   Pekerjaan                          287 non-null    object 
 4   JenjangKarir                       287 non-null    object 
 5   PerformancePegawai                 287 non-null    object 
 6   AsalDaerah                         287 non-null    object 
 7   HiringPlatform                     287 non-null    object 
 8   SkorSurveyEngagement               287 non-null    int64  
 9   SkorKepuasanPegawai                287 non-null    float64
 10  JumlahKeikutsertaanProjek          287 non-null    float64
 11  JumlahKeterlambatanSebulanTerakhir 287 non-null    float64
 12  JumlahKetidakhadiran               287 non-null    float64
 13  TingkatPendidikan                  287 non-null    object 
 14  TanggalLahir                       287 non-null    object 
 15  TanggalHiring                      287 non-null    object 
 16  TanggalPenilaianKaryawan           287 non-null    object 
 17  TanggalResign                      287 non-null    object 
dtypes: float64(4), int64(1), object(13)
memory usage: 40.5+ KB
```

From 25 to 18 features

The IkutProgramLOP feature was removed due to excessive missing values. Non-informative features such as Username, EnterpriseID, NomorHP, Email, AlasanResign were also dropped. For skewed numeric features such as JumlahKeikutsertaanProjek, JumlahKeterlambatanSebulanTerakhir, and JumlahKetidakhadiran missing values were imputed with the median to avoid distortion from outliers. Categorical features with missing values were imputed with the mode. Features like AlasanResign and TanggalResign were excluded to prevent **data leakage**.

Feature Engineering

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```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 287 entries, 0 to 286
Data columns (total 16 columns):
 #   Column                             Non-Null Count  Dtype  
---  ------                             --------------  -----  
 0   StatusPernikahan                   287 non-null    object 
 1   JenisKelamin                       287 non-null    object 
 2   StatusKepegawaian                  287 non-null    object 
 3   Pekerjaan                          287 non-null    object 
 4   JenjangKarir                       287 non-null    object 
 5   PerformancePegawai                 287 non-null    object 
 6   AsalDaerah                         287 non-null    object 
 7   HiringPlatform                     287 non-null    object 
 8   JumlahKeterlambatanSebulanTerakhir 287 non-null    float64
 9   TingkatPendidikan                  287 non-null    object 
 10  Attrition                          287 non-null    int64  
 11  Usia                               287 non-null    int64  
 12  LamaBekerja                        287 non-null    int64  
 13  BulanSejakPenilaian                287 non-null    int64  
 14  AktifScore                         287 non-null    float64
 15  SkorGabungan                       287 non-null    float64
dtypes: float64(3), int64(4), object(9)
memory usage: 36.0+ KB
```

From 18 to 16 features

The target variable Attrition was created based on whether the TanggalResign exists (1 = resigned, 0 = stayed). Date fields were converted to datetime and transformed into new features: Usia, LamaBekerja, and BulanSejakPenilaian.

Additional features included:

- *AktifScore* = JumlahKeikutSertaanProyek – JumlahKetidakhadiran
- *SkorGabungan* = 60% SkorSurveyEngagement + 40% SkorKepuasanPegawai
- Irrelevant or redundant columns were then removed to simplify the dataset.

Preprocessing

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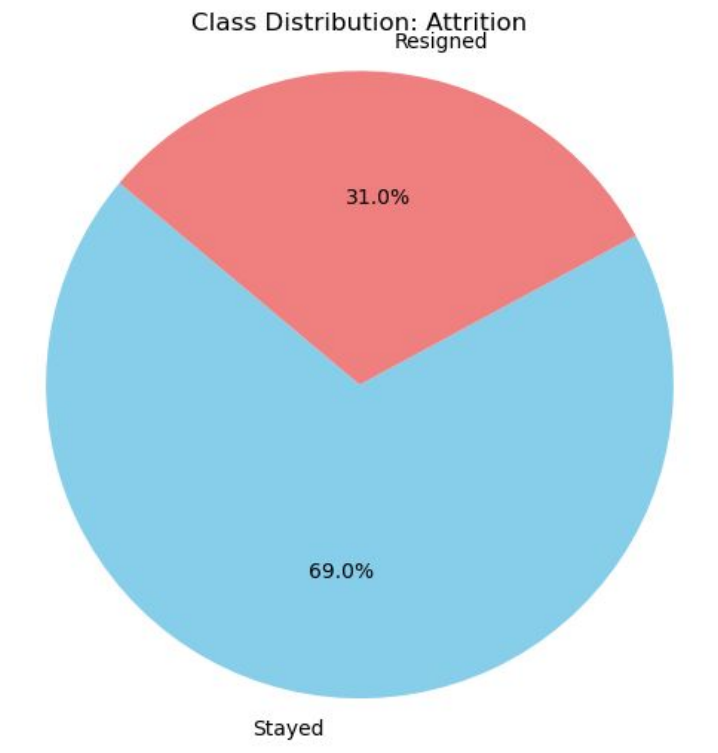
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 287 entries, 0 to 286
Data columns (total 40 columns):
 #   Column                                        Non-Null Count  Dtype  
---  ------                                        --------------  -----  
 0   scale__JumlahKeterlambatanSebulanTerakhir     287 non-null    float64
 1   scale__Usia                                   287 non-null    float64
 2   scale__LamaBekerja                            287 non-null    float64
 3   scale__BulanSejakPenilaian                    287 non-null    float64
 4   scale__AktifScore                             287 non-null    float64
 5   scale__SkorGabungan                           287 non-null    float64
 6   ord_enc__JenjangKarir                         287 non-null    float64
 7   ord_enc__PerformancePegawai                   287 non-null    float64
 8   ord_enc__TingkatPendidikan                    287 non-null    float64
 9   nom_enc__JenisKelamin_Wanita                  287 non-null    float64
 10  nom_enc__StatusPernikahan_Bercerai            287 non-null    float64
 11  nom_enc__StatusPernikahan_Lainnya             287 non-null    float64
 12  nom_enc__StatusPernikahan_Menikah             287 non-null    float64
 13  nom_enc__Pekerjaan_Data Engineer              287 non-null    float64
 14  nom_enc__Pekerjaan_DevOps Engineer            287 non-null    float64
 15  nom_enc__Pekerjaan_Digital Product Manager    287 non-null    float64
 16  nom_enc__Pekerjaan_Machine Learning Engineer  287 non-null    float64
 17  nom_enc__Pekerjaan_Product Design (UI & UX)   287 non-null    float64
 18  nom_enc__Pekerjaan_Product Design (UX Researcher) 287 non-null    float64
 19  nom_enc__Pekerjaan_Product Manager            287 non-null    float64
 20  nom_enc__Pekerjaan_Scrum Master               287 non-null    float64
 21  nom_enc__Pekerjaan_Software Architect         287 non-null    float64
 22  nom_enc__Pekerjaan_Software Engineer (Android) 287 non-null    float64
 23  nom_enc__Pekerjaan_Software Engineer (Back End) 287 non-null    float64
 24  nom_enc__Pekerjaan_Software Engineer (Front End) 287 non-null    float64
 25  nom_enc__Pekerjaan_Software Engineer (iOS)    287 non-null    float64
 26  nom_enc__StatusKepegawaian_Internship         287 non-null    float64
 27  nom_enc__StatusKepegawaian_Outsource          287 non-null    float64
 28  nom_enc__AsalDaerah_Jakarta Pusat             287 non-null    float64
 29  nom_enc__AsalDaerah_Jakarta Selatan           287 non-null    float64
 30  nom_enc__AsalDaerah_Jakarta Timur             287 non-null    float64
 31  nom_enc__AsalDaerah_Jakarta Utara             287 non-null    float64
 32  nom_enc__HiringPlatform_Diversity_Job_Fair    287 non-null    float64
 33  nom_enc__HiringPlatform_Employee_Referral     287 non-null    float64
 34  nom_enc__HiringPlatform_Google_Search         287 non-null    float64
 35  nom_enc__HiringPlatform_Indeed                287 non-null    float64
 36  nom_enc__HiringPlatform_LinkedIn              287 non-null    float64
 37  nom_enc__HiringPlatform_On-line_Web_application 287 non-null    float64
 38  nom_enc__HiringPlatform_Other                 287 non-null    float64
 39  nom_enc__HiringPlatform_Website               287 non-null    float64
dtypes: float64(40)
memory usage: 89.8 KB
```

- Numerical features (e.g., JumlahKeterlambatanSebulanTerakhir, Usia, LamaBekerja) → scaled with **RobustScaler** to reduce outlier impact.
- Ordinal features (e.g., JenjangKarir, PerformancePegawai, dan TingkatPendidikan) → encoded with **OrdinalEncoder**.
- Nominal features (e.g., JenisKelamin, StatusPernikahan, Pekerjaan) → encoded with **OneHotEncoder**, dropping the first category to avoid dummy trap.

Data Sampling

Imbalance Class



The dataset is imbalanced, with 31% attrition vs. 69% non-attrition. To address this, oversampling and undersampling methods were tested. The evaluation focused on the **F2-score**, prioritizing recall (detecting employees at risk of resigning) as an early warning system.

Data Sampling

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Data Sampling Result

	Sampling Method	precision	recall	f1	f2	roc_auc
12	SMOTEENN	0.310 ± 0.027	0.744 ± 0.139	0.436 ± 0.047	0.579 ± 0.082	0.511 ± 0.114
9	AllKNN	0.278 ± 0.108	0.675 ± 0.258	0.393 ± 0.151	0.524 ± 0.200	0.489 ± 0.105
7	EditedNearestNeighbours	0.322 ± 0.059	0.574 ± 0.112	0.411 ± 0.074	0.495 ± 0.091	0.510 ± 0.083
11	InstanceHardnessThreshold	0.334 ± 0.063	0.554 ± 0.163	0.412 ± 0.083	0.485 ± 0.117	0.511 ± 0.098
8	RepeatedEditedNearestNeighbours	0.299 ± 0.051	0.565 ± 0.229	0.376 ± 0.098	0.465 ± 0.153	0.502 ± 0.070
5	RandomUnderSampler	0.310 ± 0.096	0.475 ± 0.161	0.373 ± 0.116	0.427 ± 0.137	0.493 ± 0.119
10	NeighbourhoodCleaningRule	0.306 ± 0.056	0.463 ± 0.130	0.365 ± 0.077	0.417 ± 0.103	0.487 ± 0.102
2	SMOTE	0.310 ± 0.103	0.440 ± 0.151	0.362 ± 0.120	0.405 ± 0.135	0.492 ± 0.126
3	BorderlineSMOTE	0.315 ± 0.092	0.418 ± 0.149	0.357 ± 0.113	0.391 ± 0.132	0.505 ± 0.106
13	SMOTETomek	0.292 ± 0.119	0.407 ± 0.183	0.338 ± 0.142	0.375 ± 0.164	0.491 ± 0.127
1	RandomOverSampler	0.289 ± 0.106	0.393 ± 0.158	0.330 ± 0.122	0.364 ± 0.140	0.512 ± 0.143
4	SVMSMOTE	0.313 ± 0.124	0.351 ± 0.164	0.328 ± 0.137	0.341 ± 0.151	0.499 ± 0.113
6	TomekLinks	0.227 ± 0.248	0.126 ± 0.141	0.153 ± 0.163	0.135 ± 0.146	0.493 ± 0.098
0	No Sampling	0.194 ± 0.267	0.081 ± 0.122	0.103 ± 0.143	0.087 ± 0.126	0.497 ± 0.133

The experimental results show that the **SMOTEENN** data sampling method delivers the best performance compared to other methods, with an **F2 score of 0.679**, a **recall of 0.744**, and a **ROC AUC of 0.511**.

Considering that the main focus is to maximize the detection of employees who are likely to resign (recall) while maintaining a balanced penalty through the F2 score, **SMOTEENN is selected as the sampling method to be used in the next stage of model training.**

Model Selection

Model Selection Result

	F1-score (mean)	F2-score (mean)	Precision (mean)	Recall (mean)	ROC-AUC (mean)
KNN	0.4547	0.6389	0.3074	0.8773	0.4763
SVM	0.4242	0.5903	0.2895	0.8028	0.4363
LogReg	0.4273	0.5728	0.3011	0.7444	0.4897
CatBoost	0.4293	0.5689	0.3062	0.7306	0.5081
Ridge	0.4189	0.5532	0.2996	0.7083	0.4869
XGBoost	0.4315	0.5380	0.3267	0.6481	0.5341
RandomForest	0.4154	0.5366	0.3032	0.6699	0.5026
MLP	0.4197	0.5350	0.3105	0.6593	0.4934
ExtraTrees	0.4182	0.5329	0.3100	0.6569	0.5017
AdaBoost	0.4155	0.5275	0.3093	0.6477	0.5129
PA	0.3985	0.5113	0.2958	0.6398	0.4813
GradientBoost	0.4048	0.5091	0.3034	0.6181	0.4947
LightGBM	0.4072	0.5062	0.3105	0.6102	0.5003
DecisionTree	0.3973	0.4923	0.3025	0.5889	0.4936

Among tested models, **KNN** performed best with the highest F2-score (0.6389), followed by **SVM** (0.5903). The F2 metric was chosen because it emphasizes recall, minimizing the risk of missing at-risk employees.

Hyperparameter Tuning

Hyperparameter Tuning Result

	Best Parameters	Best Score	F1	F2	ROC-AUC	Precision	Recall
XGBoost	{'classifier__learning_rate': 0.05, 'classifie...	0.656886	0.459459	0.697674	0.407639	0.315789	1.0
SVM	{'classifier__C': 0.1, 'classifier__gamma': 's...	0.691888	0.459459	0.692308	0.386806	0.310345	1.0
LogReg	{'classifier__C': 0.1, 'classifier__l1_ratio':...	0.693247	0.459459	0.692308	0.308333	0.310345	1.0
CatBoost	{'classifier__depth': 4, 'classifier__iteratio...	0.692262	0.459459	0.674603	0.517361	0.314815	0.944444
KNN	{'classifier__metric': 'euclidean', 'classifie...	0.674915	0.459459	0.664062	0.386806	0.303571	0.944444

After tuning five top models (KNN, SVM, Logistic Regression, XGBoost, CatBoost), **XGBoost** achieved the best performance with:

- Training F2 = 0.6568
- Testing F2 = 0.6977
- F1 = 0.4600, Precision = 0.3158, Recall = 1.0000

Since recall was the priority, **XGBoost was selected as the final model**.

Model Evaluation

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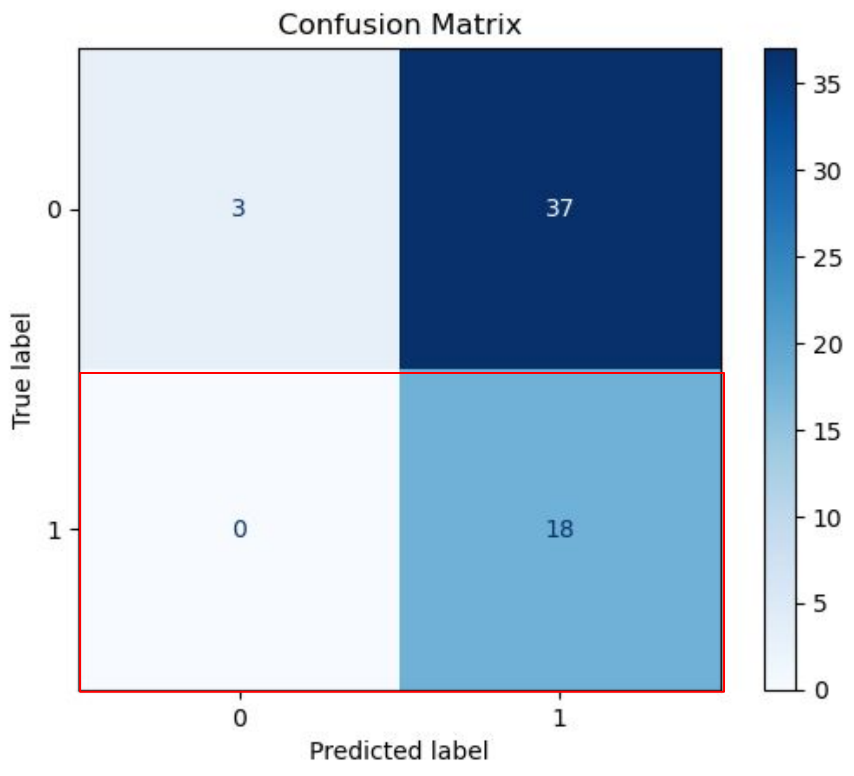
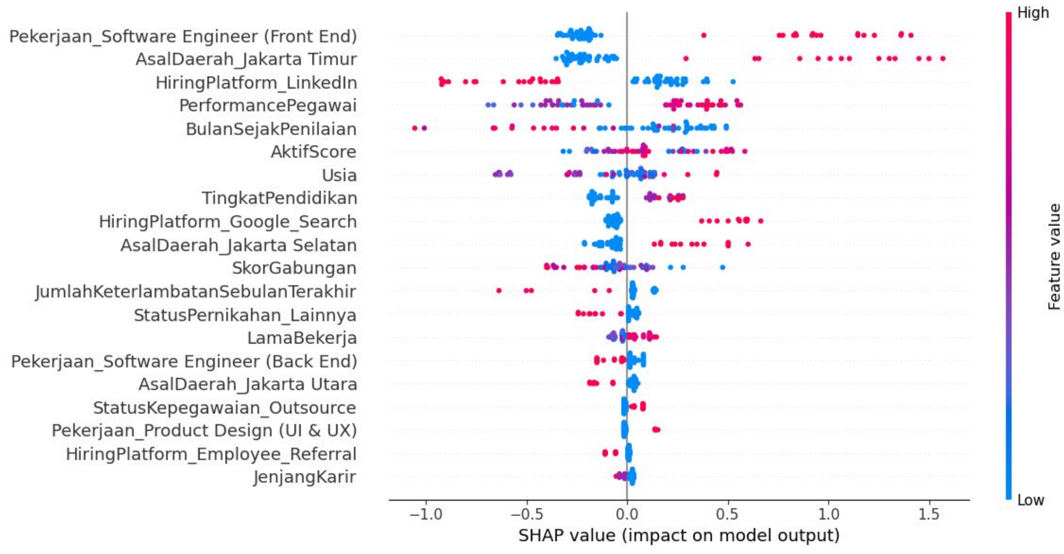
XGBoost Confusion Matrix



The confusion matrix shows **the model achieved perfect recall (1.00)**, correctly identifying all 18 employees who resigned. However, it also produced many false positives (**low precision = 0.33**), misclassifying non-resigners as at-risk. While the model is highly sensitive, **making it useful for early intervention**, it lacks specificity in distinguishing actual stayers.

Model Interpretability

SHAP Value Summary Plot



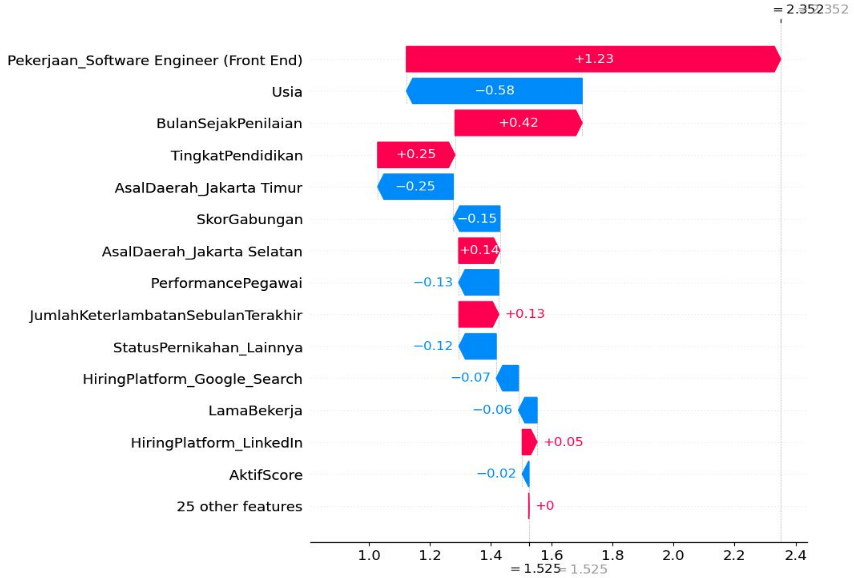
SHAP analysis highlighted key attrition drivers:

- Being a **Front End Engineer** *significantly increases resignation risk*.
- Employees from **East Jakarta** and those recruited via **LinkedIn** showed *higher attrition likelihood.*
- **High-performing employees** paradoxically face *higher risk of leaving*.
- **Longer gaps since the last evaluation** correlate with *higher attrition*.
- **Lower Activity Score** strongly signals *risk*.

Model Interpretability

An Employee's Prediction Simulation

```
Informasi Karyawan:
-----------
StatusPernikahan                                        Lainnya
JenisKelamin                                             Wanita
StatusKepegawaian                                      FullTime
Pekerjaan                           Software Engineer (Front End)
JenjangKarir                                          Mid_level
PerformancePegawai                                        Biasa
AsalDaerah                                      Jakarta Selatan
HiringPlatform                                           Indeed
JumlahKeterlambatanSebulanTerakhir                          0.0
TingkatPendidikan                                        Doktor
Usia                                                         46
LamaBekerja                                                  12
BulanSejakPenilaian                                          69
AktifScore                                                 -6.0
SkorGabungan                                                4.0
```



In an example case, **an employee showed a high attrition score** (**2.35** vs. **baseline 1.52**). Main risk drivers: *role as Front End Engineer*, *long gap since last evaluation*, *higher education level*, *frequent lateness*, and *certain regional background*. Protective factors included *age*, *good performance*, *engagement score*, and *longer tenure*—but **these were insufficient to offset the risks**.

Recommendations

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1. **Focus on Front End Engineers and Young Talent**

   Provide structured career paths, mentorship programs, and balanced workloads to reduce burnout.

2. **Accelerate Evaluations and Career Development**

   Conduct quarterly performance reviews with clear feedback, promotions, and project opportunities.

3. **Location- and Performance-Based Interventions**
   - Introduce flexible policies (e.g., hybrid work, commuting support) for employees in high-cost areas like South Jakarta.
   - Use lateness and absenteeism data as early warning indicators to trigger retention actions.
4. **Foster a Healthy Work Culture**

   Address toxic cultural factors through leadership training, anonymous feedback systems, and recognition programs.

5. **Leverage Predictive Analytics for HR Decisions**

   Integrate the model into HR systems to continuously monitor attrition risk and enable proactive management actions.

Thank You