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Machine Learning-Driven Employee Layoff Prediction Using Social Network Analysis

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Abstract
Managing workforce stability during organizational changes is a critical challenge for modern enterprises. This study proposes an intelligent prediction system to identify employees who are at potential risk of layoffs by analysing historical employee data and workplace interaction patterns. The model integrates multiple factors, including demographic details, job history, performance evaluations, salary information, and career growth indicators, to build a comprehensive employee profile. In addition, Social Network Analysis (SNA) techniques are employed to capture employee connectivity and influence within the organization using metrics such as degree centrality, betweenness centrality, and closeness centrality. After preprocessing and selecting relevant features, a Random Forest classifier is developed to detect patterns associated with layoff events. The model's performance is evaluated using standard metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. Experimental results indicate that the inclusion of network-based features improves the model's ability to identify at-risk employees more effectively compared to traditional approaches. The proposed system provides valuable insights that can support organizations in proactive decision-making, enabling timely interventions, better workforce planning, and improved employee retention strategies.
Keywords: *Machine Learning, Employee Layoff Prediction, Social Network Analysis (SNA), Random Forest, Degree Centrality, HR Analytics, Workforce Risk Assessment, Feature Engineering, Predictive Analytics, Employee Retention.*

1. Introduction
The increasing availability of workforce data has enabled organizations to employ analytical techniques for improving strategic human resource management and workforce planning. Organizations generate large volumes of employee-related data through performance evaluations, communication platforms, attendance systems, and workforce management applications. Extracting meaningful insights from these data sources has become essential for improving organizational effectiveness and supporting strategic workforce planning. One of the major challenges faced by organizations is identifying workforce risks, such as employee layoffs, workforce restructuring, and talent loss, before they negatively impact business operations. Machine Learning techniques have demonstrated significant potential in addressing workforce management challenges. Predictive models trained on historical employee data can uncover hidden patterns within large and complex datasets. By learning from historical employee information, Machine Learning models can estimate the likelihood of future workforce outcomes and support objective, evidence-based decision-making (Burange et al., 2025; Prasad et al., 2025). The proposed framework integrates employee demographic attributes, performance indicators, and organizational interaction metrics to identify workforce vulnerability and support strategic retention initiatives. The integration of

network-based features with conventional employee attributes enhances the predictive capability of the system and provides a comprehensive understanding of workforce dynamics. Furthermore, the framework incorporates automated data preprocessing, feature extraction, model development, performance evaluation, visualization, and reporting techniques to generate reliable predictions and support effective decision-making. By leveraging advanced analytics and intelligent prediction models, the system contributes to improved workforce planning, employee retention initiatives, and organizational sustainability. The primary contribution of this study is the integration of Social Network Analysis(SNA) metrics with traditional employee and performance-related attributes for employee layoff prediction. Unlike existing approaches that mainly focus on demographic and organizational variables, the proposed framework incorporates employee connectivity, influence, and interaction patterns through network centrality measures. This combined feature representation enables the prediction model to capture both individual performance characteristics and organizational relationship structures. Furthermore, the proposed framework employs a Random Forest classifier enhanced with network-based feature engineering to improve prediction reliability. The integration of SNA-derived indicators contributes additional contextual information that is often overlooked in conventional workforce analytics models. As a result, the system provides a more comprehensive assessment of layoff risk and supports proactive workforce management decisions.

1.1.Related Works

Recent studies have demonstrated the effectiveness of machine learning techniques in employee attrition and workforce risk prediction. Guerranti and Dimitri (2023), Malik et al. 2022), and Kim et al. 2023) explored ensemble-based approaches and reported that algorithms such as Random Forest, XBoost, and stacking models provide improved predictive capability when compared with conventional classification techniques. Their findings mainly highlight the importance of employee satisfaction, compensation, work experience, and workplace relationships in predicting workforce transitions. In their work, Borse et al. (2024), Park et al. (2024), and Krishna et al. (2024) focused on identifying behavioural and organizational factors associated with employee turnover. These studies emphasize that predictive analytics can assist organizations in recognizing potential workforce instability at an early stage and support the development of targeted employee retention strategies. Their results further demonstrate the value of machine learning in strategic workforce planning and human resource decision-making. Beyond traditional HR attributes, Borgatti et al. (2023) and Kautz and Mahnke 2023) highlighted the significance of Social Network Analysis in understanding employee behaviour and retention patterns. Their work showed that network measures such as centrality and communication density can provide additional insights into workforce dynamics. However, most existing studies rely primarily on demographic and performance-related variables, with limited consideration of employee interaction structures. To address this gap, the present study integrates Social Network Analysis metrics with conventional HR features to improve layoff risk prediction and provide a more comprehensive assessment of workforce vulnerability.

1.2.Proposed Methodology

The proposed Machine Learning-Driven Employee Layoff Prediction framework is designed to identify employees who may be at risk of layoffs by analysing employee information, performance records, and organizational interaction patterns. The methodology consists of five major stages, as described below.

1.3.Data Collection and Preprocessing

Employee-related data are collected from multiple organizational datasets, including employee records, performance evaluations, communication

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data, and risk-related information. The collected data are then preprocessed by handling missing values, removing duplicate records, and converting categorical attributes into numerical formats. This process ensures data quality and prepares the dataset for further analysis (Habous et al., 2021).

1.4. Social Network Analysis and Feature Engineering

To capture employee interaction behaviour within the organization, Social Network Analysis (SNA) is applied to communication and collaboration data. Employees are represented as nodes, while their interactions form network connections. Important network metrics such as Degree Centrality, Betweenness Centrality, and Closeness Centrality are extracted. These SNA features are combined with traditional HR attributes, including tenure, salary, performance scores, and project participation, to create a comprehensive feature set for prediction. (Borgatti et al., 2023; Kautz & Mahnke, 2023).

- $DC(v)=N-1/deg(v)$
- $deg(v)$ = number of direct connections
- N = total employees

1.5. Model Development and Training

The processed dataset is used to develop a predictive model based on the Random Forest algorithm. Random Forest is selected because of its ability to handle large datasets, capture complex relationships among variables, and provide reliable classification performance. The model is trained using historical employee data to learn patterns associated with layoff outcomes.

$$\tilde{Y} = \text{mode}\{T1(x), T2(x), \ldots, Tn(x)\}$$

where:

- $\acute{Y}$ represents the final predicted class label.
- $Ti(x)$ denotes the prediction generated by the ith decision tree for input sample x.
- n is the total number of decision.
- mode indicates the majority voting operation used to determine the final prediction.

1.6. Model Evaluation and Prediction

The trained model is evaluated using testing data to measure its effectiveness and reliability. Performance is assessed using evaluation metrics such as Accuracy, Precision, Recall, and F1-Score. Once validated, the model predicts the layoff risk of employees by analysing both performance-related and network-based characteristics.

1.7. Visualization and Decision Support

The prediction results are presented through visualization and reporting tools, including dashboards, charts, and employee risk reports. These outputs help HR professionals identify high-risk employees, understand workforce trends, and support data-driven decision-making.

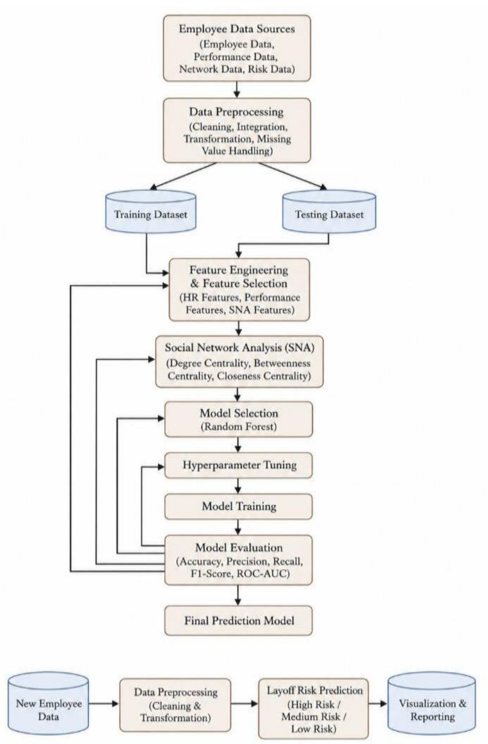

Figure 1 Architecture of the Employee Layoff Risk Prediction Model

2. Dataset

The dataset used in this study consists of historical employee records containing both demographic and employment-related information. Each employee entry includes attributes such as age,

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gender, marital status, education level, job role, department, salary, and tenure within the organization. These features provide a detailed representation of employee backgrounds and career profiles, which are essential for analysing workforce trends and identifying factors associated with layoff decisions. In addition to employee profile data, the dataset incorporates performance evaluation scores, employee satisfaction measures, departmental and organizational performance indicators, and records of recent organizational changes. Historical layoff information, including the reasons for workforce reductions, is used as the target variable for prediction. By combining these factors, the dataset enables the identification of meaningful patterns and relationships that support the development of an effective employee layoff prediction model,As shown in Figure 2 Employee Layoff Prediction Dataset[1 – 10].

DATASET

The dataset contains employee records with 11 predictive attributes and 1 target variable (LayoffRisk).

EmployeeID	Tenure (Years)	Performance Score	BaseSalary (USD)	Projects Completed	Training Completed	Degree Centrality	Betweenness Centrality	Closeness Centrality	Emails Per Day	Unique Contacts	Cross Dept Collaborations	LayoffRisk (Target)
E001	2.1	3.2	45000	3	2	0.35	0.12	0.48	25	45	5	0
E002	5.8	4.1	62000	6	4	0.42	0.18	0.51	32	60	8	0
E003	1.3	2.6	38000	1	1	0.22	0.05	0.31	15	28	2	1
E004	3.6	3.8	52000	4	3	0.38	0.11	0.46	28	50	6	0
E005	7.2	4.5	75000	7	5	0.48	0.22	0.55	40	72	10	0
E006	0.9	2.1	35000	0	0	0.18	0.03	0.27	10	20	1	1
E007	4.4	3.9	58000	5	2	0.41	0.14	0.49	30	55	7	0
E008	6.1	4.2	68000	6	4	0.46	0.19	0.53	36	65	9	0
E009	2.7	2.9	41000	2	1	0.25	0.07	0.33	18	32	3	1
E010	3.2	3.5	49000	3	2	0.33	0.10	0.44	22	40	4	0
...	...	...	...	...	...	...	...	...	...	...	...	...
E491	5.0	3.7	54000	4	3	0.39	0.13	0.47	27	48	6	0
E492	1.7	2.4	36000	1	1	0.21	0.04	0.29	13	24	2	1
E493	6.8	4.3	72000	6	4	0.47	0.21	0.54	38	68	9	0
E494	2.3	3.1	43000	2	1	0.28	0.08	0.35	16	30	3	1
E495	4.9	3.6	56000	4	3	0.37	0.12	0.45	24	46	5	0
E496	3.8	3.4	50000	3	2	0.32	0.09	0.41	20	38	4	0
E497	0.8	2.0	34000	0	0	0.16	0.02	0.24	9	18	1	1
E498	5.5	4.0	61000	5	3	0.44	0.16	0.50	31	57	7	0
E499	2.0	2.7	40000	1	1	0.23	0.06	0.32	14	26	2	1
E500	6.3	4.1	67000	6	4	0.45	0.17	0.52	34	63	8	0

Total Records: 500 Employees | Predictive Attributes: 11 | Target Variable: LayoffRisk (0 = No Risk, 1 = High Risk)

Figure 2 Employee Layoff Prediction Dataset

3. Machine Learning Framework for Employee Layoff Risk Prediction

3.1. Data Collection and Predictive Analytics Framework

The proposed framework employs a Random Forest classifier to analyze employee demographic, performance, and organizational attributes. By combining multiple decision trees, the model captures complex relationships among workforce variables and generates reliable layoff risk predictions [11].

3.2.Feature Engineering and Organizational Network Analysis

To improve predictive effectiveness, the proposed system incorporates Social Network Analysis (SNA) alongside traditional human resource metrics. Organizational communication and collaboration patterns are transformed into measurable network features such as degree centrality, betweenness centrality, and closeness centrality. These indicators reflect an employee’s connectivity, influence, and position within the workplace network. The collected network metrics are integrated with performance-related variables, including project completion rates, training participation, salary, and tenure. Furthermore, feature engineering techniques are applied to enhance data quality and relevance. Methods such as Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE) are utilized to identify the most informative attributes while reducing redundancy. This integrated feature set allows the model to evaluate both individual performance and organizational relationships when predicting layoff risk[12].

3.3.Validation Strategy and Model Performance Evaluation

A comprehensive validation strategy is employed to ensure the reliability and generalizability of the prediction model. The dataset is divided into training and testing subsets, and K-Fold Cross-Validation is used to assess model performance across multiple data partitions. To further enhance predictive accuracy, Grid Search Optimization is applied for selecting optimal model parameters. The effectiveness of the model is evaluated using performance metrics such as accuracy, precision, recall, F1-score, confusion matrix analysis, and ROC curve assessment. Data preprocessing techniques, including feature scaling and standardization, are incorporated to improve model

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efficiency and consistency. This optimization framework ensures that the system delivers dependable and actionable insights for proactive workforce management [13].

4. Results And Discussion

4.1. Results

The proposed Employee Layoff Prediction System was evaluated using a diverse set of employee-related attributes, including performance score, completed projects, salary, years of experience, department rating, job satisfaction, training hours, promotion history, work-life balance, and cross-departmental engagement. These features were processed and analysed using the Random Forest classification algorithm to estimate the likelihood of employee layoffs. The inclusion of multiple workforce indicators enabled the model to assess employee status from both performance and organizational perspectives. The proposed model was compared with alternative classification techniques including Support Vector Machine (SVM), Decision Tree, and Logistic Regression. Experimental findings indicated that the proposed ensemble-based approach achieved superior predictive performance owing to its ability to capture nonlinear relationships among employee attributes and network-based features [14].

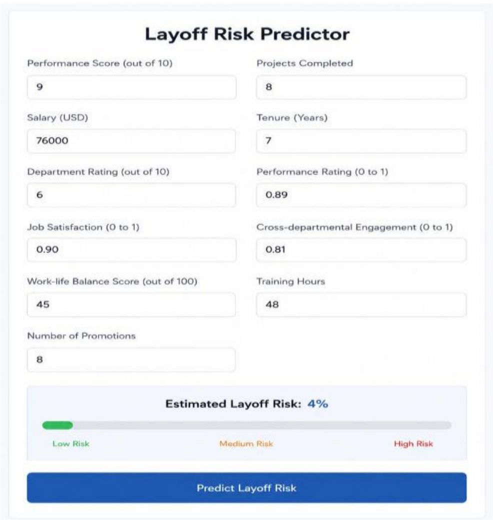

Figure 3 Implementation Interface for Employee Layoff Risk Assessment

The experimental analysis generated a layoff risk prediction of 4% for the selected employee profile, indicating a low probability of workforce separation. The employee demonstrated strong professional performance through a performance score of 9/10, completion of eight projects, and a performance rating of 0.89. In addition, seven years of organizational experience, 48 hours of training participation [15], eight promotions, and a job satisfaction score of 0.90 contributed significantly to the favourable prediction outcome. These results demonstrate the capability of the proposed framework to identify employees with strong retention potential, as shown in Figure 3 Implementation Interface for Employee Layoff Risk Assessment [16].

5. Discussion

The findings indicate that employee retention is influenced by a combination of performance excellence, organizational engagement, and continuous skill development. Feature importance analysis identified performance score, job satisfaction, tenure, degree centrality, and training participation as the most influential predictors. Employees exhibiting strong performance and active workplace connectivity were associated with lower layoff risk, highlighting the importance of both individual achievement and organizational involvement.

Moreover, the results highlight the effectiveness of the Random Forest algorithm in identifying complex patterns within employee data. By simultaneously considering multiple workforce attributes, the proposed framework provides a comprehensive approach for assessing layoff susceptibility and employee retention trends.This observation is consistent with findings reported in previous workforce analytics studies (Kim et al., 2023; Park et al., 2024).

Conclusion

This study presents a machine learning-based framework for assessing employee layoff risk through the integration of workforce attributes and organizational interaction patterns. By analysing historical employee records, performance indicators, and predictive analytics, the proposed framework assists organizations in identifying potential layoff risks with greater accuracy. Experimental results demonstrate that integrating traditional HR attributes with Social Network Analysis metrics improves the identification of employees who may be vulnerable to workforce reduction. Through the use of advanced machine learning algorithms, the framework effectively uncovers relationships among employee-related factors and generates dependable predictions that can support strategic human resource planning. Additionally, its visualization and reporting capabilities enhance the accessibility and interpretability of prediction outcomes for HR professionals. The present study is limited by its dependence on historical organizational data and the availability of communication network information. Prediction accuracy may vary across industries and organizational structures. Future research may investigate deep learning approaches, real-time workforce analytics, explainable AI techniques, and larger multi-organizational datasets to enhance model generalizability and interpretability. A key strength of the proposed framework lies in its ability to combine employee performance indicators with organizational interaction patterns derived from Social Network Analysis. This integration enables a more holistic evaluation of workforce behaviour and improves the identification of employees who may be vulnerable to layoffs compared with approaches that rely solely on traditional HR metrics. Beyond its predictive functionality, the framework contributes to a more proactive and employee-focused approach to workforce management. By identifying individuals who may be vulnerable to workforce reduction, organizations can implement timely interventions such as training programs, mentoring opportunities, and career development initiatives. This enables better alignment between employee growth and organizational objectives while promoting fairness, transparency, and employee well-being. The study highlights the value of data-driven decision-making in improving workforce stability and organizational effectiveness. The developed framework can assist organizations in identifying workforce vulnerabilities and supporting proactive retention strategies.

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