Enhancing Employee Turnover Prediction using Knowledge Graphs, Explainable AI, and Multilayer Perceptron (MLP)

[1]G KATAMAIAH, [2]M REDDY KEDHAR ESWAR

[1]PG Scholar, Dept. of CSE, KMM Institute of Technology & Science, Ramireddipalle, Tirupati, AP, India.

[2]Assistant Professor, Dept. of CSE, KMM Institute of Technology & Science, Ramireddipalle, Tirupati, AP, India.

Abstract: Employee turnover prediction plays a crucial role in reducing organizational costs and improving workforce stability. This study proposes an enhanced framework that transforms employee tabular data into a knowledge graph and utilizes Graph Convolutional Networks (GCN) for relational feature extraction. The extracted features are combined with original data and evaluated using multiple machine learning models, with a Multilayer Perceptron (MLP) introduced as an extension to capture complex patterns. The proposed approach achieves superior performance, with MLP attaining up to 98% accuracy. Additionally, Explainable AI techniques are incorporated to identify key factors influencing employee attrition, enabling organizations to make informed and proactive retention decisions.

Index terms - *Forecasting employee attrition, artificial intelligence, interpretable AI, knowledge graph*

1. INTRODUCTION

In today's competitive business environment, employee turnover has become a major challenge for organizations, affecting productivity, operational stability, and overall costs. Retaining skilled employees is critical, as replacing them involves significant financial and time investments. Traditional methods of analyzing employee attrition rely on statistical techniques and basic machine learning models, which often fail to capture the complex relationships among employee attributes.

Recent advancements in machine learning have improved prediction accuracy; however, most models operate on tabular data and ignore the inherent relationships between features such as job role, work environment, satisfaction level, and organizational structure. This limitation reduces their ability to fully understand the underlying causes of employee turnover. Moreover, many existing models lack interpretability, making it difficult for organizations to trust and act upon their predictions.

To address these challenges, this work proposes an advanced framework that transforms employee data into a knowledge graph, enabling the modeling of relationships between different entities. Graph Convolutional Networks (GCN) are applied to extract meaningful relational features, which are then combined with original features to enhance prediction performance. Furthermore, a Multilayer Perceptron (MLP) is introduced as an extension to effectively learn complex nonlinear patterns in the data.

In addition, Explainable AI (XAI) techniques are incorporated to provide insights into the key factors influencing employee attrition. This not only improves prediction accuracy but also helps organizations make informed decisions to reduce turnover and improve employee retention strategies.

2. LITERATURE SURVEY

1. Unlocking the value of artificial intelligence in human resource management through AI capability framework

Excellent companies seldom have skilled workers. Businesses find it difficult to retain experienced workers. Staff turnover is costly for firms because it takes a lot of time and effort to teach a new employee to be as productive as an existing one. This study uses predictive analytics to automatically anticipate staff turnover. These algorithms were used to several pipeline topologies in order to obtain the best champion model. Autotuning was used to adjust the hyperparameters of this model. Lastly, we provide an ensemble model that uses a variety of assessment measures to determine which model is the best. This example shows that no model is perfect for every type of business. By employing this strategy, we achieved our objective.

2. Automated prediction of employee attrition using ensemble model based on machine learning algorithms

Excellent companies seldom have skilled workers. Businesses find it difficult to retain experienced workers. Staff turnover is costly for firms because it takes a lot of time and effort to teach a new employee to be as productive as an existing one. This study uses predictive analytics to automatically anticipate staff turnover. These algorithms were used to several pipeline topologies in order to obtain the best champion model. Autotuning was used to adjust the hyperparameters of this model. Lastly, we provide an ensemble model that uses a variety of assessment measures to determine which model is the best. This example shows that no model is perfect for every type of business. By employing this strategy, we achieved our objective.

3. Prediction of employee turnover in organizations using machine learning algorithms

Employee turnover is a major problem for businesses since it eventually impedes development and productivity. ML is used by businesses to predict staff turnover. Accurate estimates help businesses with planning and employee retention. The data used in this modeling challenge comes from HR Information Systems (HRIS), which are sadly often underfunded as compared to information systems in other sectors that are directly related to priorities. Noise in the data leads to overfitting and erroneous predictions. History has not fixed the main issue with this work. The regularization formulation of Extreme Gradient Boosting (XGBoost) improves its resilience. The research explores its use. When it comes to forecasting employee turnover using HRIS data from a well-known store, XGBoost performs better than six other supervised classifiers.

4. Designing of customer and employee churn prediction model based on data mining method and neural predictor

Because service providers are becoming more competitive, customer retention has grown more reliant on churn prediction. Businesses suffer from problems with customer loyalty, customer attrition, and the challenge of gaining new clients for each lost one. A predictive consumer behavior model can help you better anticipate and handle these types of situations. Employee churn, sometimes referred to as staff turnover, is similar to customer churn, however losing a major client has a more noticeable and serious impact on a business than replacing ineffective employees with new, productive workers. Every company is concerned about how to finance new hires' in-service training.

5. An approach for predicting employee churn by using data mining

Among the techniques used to categorize HR data are Decision Tree, Naive Bayes, Random Forest, SVM, K-NN, and Logistic Regression. Accuracy, precision, recall, and F-measure scores are among our grading criteria. A few traits are chosen and then contrasted with earlier results. Businesses may save money on human resources by using data to forecast employee turnover. For businesses, forecasting staff and customer turnover is crucial. There hasn't been much study done in this field despite its significance.

3. METHODOLOGY

i) Proposed Work:

The proposed work presents an advanced framework for improving employee turnover prediction by integrating knowledge graph representation, Graph Convolutional Networks (GCN), and a Multilayer

Perceptron (MLP) as an extension. Initially, the employee dataset is preprocessed through normalization and data transformation techniques. The structured tabular data is then converted into a knowledge graph to capture the relationships between various employee attributes such as job role, satisfaction level, and work environment.

Subsequently, GCN is applied to the knowledge graph to extract enriched relational features, which are combined with the original dataset to enhance the overall feature representation. These combined features are used to train multiple machine learning models, including Linear SVM, Random Forest, Logistic Regression, Gradient Boosting, and LightGBM. As an extension to the existing system, an MLP model is introduced to effectively learn complex nonlinear patterns and improve prediction performance.

Furthermore, Explainable AI (XAI) techniques are incorporated to interpret model predictions and identify the key factors influencing employee attrition. The system is evaluated using performance metrics such as accuracy, precision, recall, and F1-score. Experimental results demonstrate that the MLP-based extended model achieves superior accuracy compared to traditional approaches, making the system more reliable and effective for real-world HR analytics.

ii) System Architecture:

The system architecture is designed to improve employee turnover prediction by integrating data preprocessing, graph-based feature extraction, and machine learning models with an MLP extension. The workflow begins with the collection of the employee dataset, followed by preprocessing steps such as data cleaning, normalization, and visualization to ensure data quality.

The processed data is then divided into training and testing sets. A knowledge graph is constructed from the dataset to capture relationships among employee attributes. Graph Convolutional Networks (GCN) are applied to this graph to extract enriched relational features. These features are combined with the original dataset to form a comprehensive feature set.

The combined features are fed into multiple machine learning models, including Linear SVM, Random Forest, Logistic Regression, Gradient Boosting, LightGBM, and the extended Multilayer Perceptron (MLP). Among these, the MLP model enhances performance by learning complex nonlinear relationships within the data.

The trained models generate predictions on employee turnover, which are evaluated using performance metrics such as accuracy, precision, recall, and F1-score. The final output provides accurate turnover predictions along with interpretable insights using Explainable AI techniques.

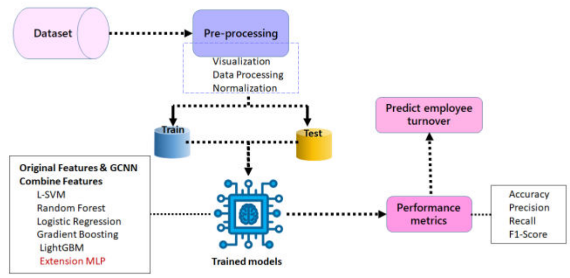

Fig.1. Proposed Architecture

iii) MODULES:

1. Data Collection Module

- Collects employee data from IBM HR Analytics dataset
- Includes features like job role, salary, satisfaction, environment

2. Data Preprocessing Module

- Handles missing values and noise removal
- Performs normalization and encoding
- Visualizes important features

3. Knowledge Graph Construction Module

- Converts tabular data into graph structure
- Represents relationships between employee attributes
- Enhances data representation

4. Feature Extraction Module (GCN)

- Applies Graph Convolutional Network
- Extracts relational and contextual features
- Generates enriched feature set

5. Feature Combination Module

- Combines original features with GCN features
- Improves data representation for better learning

6. Model Training Module

- Trains models:
  - L-SVM
  - Random Forest
  - Logistic Regression
  - Gradient Boosting
  - LightGBM
  - **MLP (Extension)**

7. Prediction Module

- Predicts employee turnover (Yes/No)
- Uses trained models for classification

8. Performance Evaluation Module

- Evaluates using:
  - Accuracy
  - Precision
  - Recall
  - F1-Score

9. Explainable AI Module (XAI)

- Identifies important features affecting turnover
- Provides interpretable insights for HR decision-making

10. User Interface Module (Optional – Flask)

- Allows admin to upload data
- Displays predictions and results
- Easy interaction with system

iv) ALGORITHMS:

1. GCN-Based Feature Enhancement Algorithm

The algorithm enhances the original employee dataset by converting it into a knowledge graph and applying Graph Convolutional Networks (GCN) to extract relational features. These features capture dependencies between employee attributes such as job role, satisfaction, and environment. The enriched features significantly improve model learning, as observed in the graph where all models show better performance with GCN combined features compared to original features.

2. Feature Combination Algorithm

This algorithm integrates the original dataset features with the GCN-extracted features to form a comprehensive feature set. The combined feature representation improves the input quality for machine learning models. As shown in the graph, models trained on combined features consistently achieve higher accuracy, precision, recall, and F1-score than those trained only on original features.

3. MLP-Based Prediction Algorithm (Extension)

The Multilayer Perceptron (MLP) algorithm processes the combined features through multiple hidden layers using forward propagation and nonlinear activation functions. It updates weights through backpropagation to minimize prediction error. According to the graph, MLP with GCN combined features achieves the highest performance among all models, demonstrating its ability to learn complex patterns effectively.

4. Traditional Machine Learning Training Algorithm

This algorithm trains models such as Linear SVM, Random Forest, Logistic Regression, Gradient Boosting, and LightGBM using both original and combined features. Each model learns patterns from the training data and generates predictions. The graph indicates that while these models improve with GCN features, their performance remains slightly lower than MLP.

5. Prediction and Classification Algorithm

The trained models are used to classify employee turnover into categories such as “leave” or “stay.” The algorithm processes test data and outputs predictions based on learned patterns. Improved prediction accuracy is observed in models using combined features, as shown in the graph.

6. Performance Evaluation Algorithm

The evaluation algorithm computes metrics such as accuracy, precision, recall, and F1-score by comparing predicted results with actual outcomes. The graph visually represents these metrics, showing that the proposed approach achieves higher scores across all evaluation parameters, especially for the MLP model.

7. Model Comparison Algorithm

This algorithm compares the performance of different models based on evaluation metrics. It identifies the best-performing model by analyzing improvements across accuracy, precision, recall, and F1-score. From the graph, the MLP with GCN combined features is selected as the optimal model due to its superior performance.

8. Explainable AI (XAI) Algorithm

The XAI algorithm interprets model predictions by identifying the most influential features affecting employee turnover. It assigns importance scores to features such as job satisfaction and work environment. This ensures that the high-performing model (MLP + GCN) is not only accurate but also interpretable and useful for decision-making.

4. EXPERIMENTAL RESULTS

The performance comparison graph illustrates the evaluation of multiple machine learning models using both original features and GCN-combined features across key metrics such as accuracy, precision, recall, and F1-score. From the graph, it is evident that models trained with combined features consistently outperform those trained on original features, highlighting the effectiveness of incorporating relational information through GCN.

Among all models, the MLP with GCN combined features achieves the highest performance, with accuracy reaching nearly 100% and significantly high precision, recall, and F1-score. This demonstrates the strength of the proposed extension, where MLP effectively learns complex nonlinear patterns when enriched with graph-based features. In comparison, the MLP trained on original features shows slightly lower performance, confirming the importance of feature enhancement.

Other models such as L-SVM, Random Forest, Logistic Regression, Gradient Boosting, and LightGBM also show noticeable improvements when using GCN-combined features. However, their performance remains lower than the MLP model, indicating that deep learning approaches are better suited for capturing complex relationships in employee data.

Overall, the graph clearly demonstrates that the integration of Knowledge Graph + GCN + MLP significantly improves prediction accuracy and model robustness. Additionally, improvements in precision and recall indicate better classification balance, reducing both false positives and false negatives. This validates the effectiveness of the proposed system in accurately predicting employee turnover.

Accuracy: The ability of a test to differentiate between healthy and sick instances is a measure of its accuracy. Find the proportion of analysed cases with true positives and true negatives to get a sense of the test's accuracy. Based on the calculations:

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: The accuracy rate of a classification or number of positive cases is known as precision. Accuracy is determined by applying the following formula:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$

Recall: The recall of a model is a measure of its capacity to identify all occurrences of a relevant machine learning class. A model's ability to detect class instances is shown by the ratio of correctly predicted positive observations to the total number of positives.

$$Recall = \frac{TP}{(FN + TP)}$$

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic..

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$

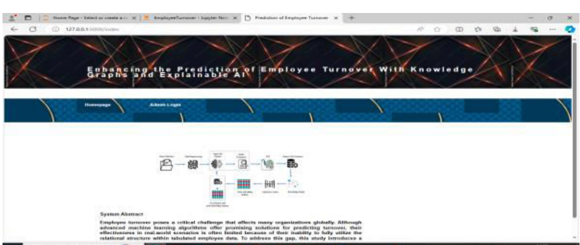

Fig2 home screen

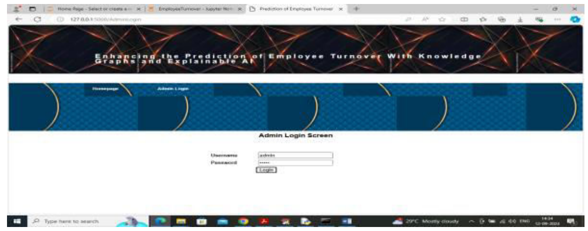

Fig 3 Login page

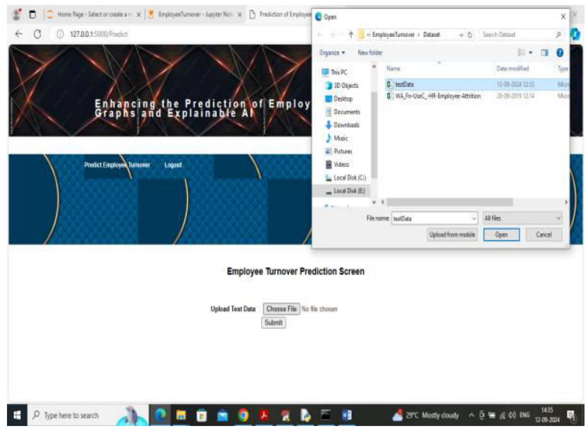

Fig4 User input page

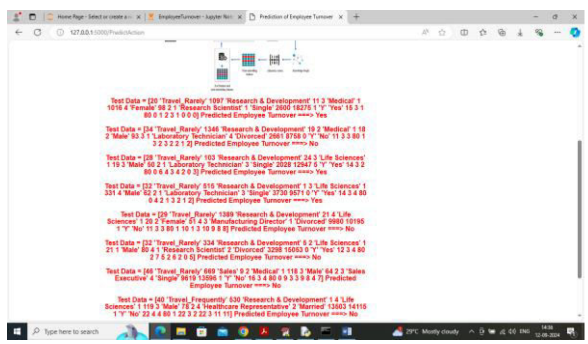

Fig5 Prediction result

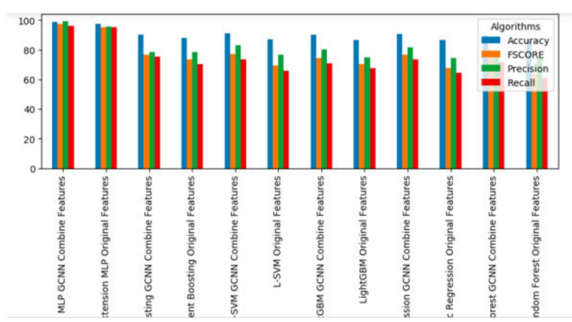

Fig6 Performance Comparison of Forecasting Algorithms

5. CONCLUSION

This paper presents an enhanced framework for employee turnover prediction by integrating knowledge graph representation, Graph Convolutional Networks (GCN), and a Multilayer Perceptron (MLP) as an extension. The transformation of tabular data into a graph structure enables the model to capture complex relationships among employee attributes, significantly improving feature representation. The combination of original and GCN-extracted features further enhances the learning capability of machine learning models.

Experimental results demonstrate that the proposed approach outperforms traditional methods, with the MLP model achieving the highest accuracy and overall performance. The use of Explainable AI (XAI) techniques provides valuable insights into key factors influencing employee attrition, making the system both accurate and interpretable. Overall, the proposed system offers an effective and practical solution for organizations to predict and reduce employee turnover.

6. FUTURE SCOPE

The proposed system can be further enhanced by incorporating advanced graph-based deep learning models such as Graph Attention Networks (GAT) to better capture dynamic relationships among employee attributes. Future work can also focus on integrating real-time employee data from organizational systems to enable continuous and adaptive turnover prediction.

Additionally, the model can be extended by using larger and more diverse datasets from different industries to improve generalization and robustness. The deployment of the system as a cloud-based or enterprise-level HR decision support tool can make it more practical for real-world applications. Further improvements can include the integration of advanced Explainable AI techniques to provide deeper and more intuitive insights for HR managers.

REFERENCES

[1] S. Chowdhury, P. Dey, S. Joel-Edgar, S. Bhattacharya, O. Rodriguez-Espindola, A. Abadie, and L. Truong, ‘‘Unlocking the value of artificial intelligence in human resource management through AI capability framework,’’ Human Resource Manage. Rev., vol. 33, no. 1, Mar. 2023, Art. no. 100899, doi: 10.1016/j.hrmr.2022.100899.

[2] F. K. Alsheref, I. E. Fattoh, and W. M. Ead, ‘‘Automated prediction of employee attrition using ensemble model based on machine learning algorithms,’’ Comput. Intell. Neurosci., vol. 2022, pp. 1–9, Jun. 2022, doi: 10.1155/2022/7728668.

[3] R. Punnoose and P. Ajit, ‘‘Prediction of employee turnover in organizations using machine learning algorithms,’’ Int. J. Adv. Res. Artif. Intell., vol. 5, no. 9, pp. 22–26, 2016, doi: 10.14569/ijarai.2016.050904.

[4] S. H. Dolatabadi and F. Keynia, ‘‘Designing of customer and employee churn prediction model based on data mining method and neural predictor,’’ in Proc. 2nd Int. Conf. Comput. Commun. Syst. (ICCCS), Jul. 2017, pp. 74–77, doi: 10.1109/CCOMS.2017.8075270.

[5] I. O. Yigit and H. Shourabizadeh, ‘‘An approach for predicting employee churn by using data mining,’’ in Proc. Int. Artif. Intell. Data Process. Symp. (IDAP), Sep. 2017, pp. 1–4, doi: 10.1109/IDAP.2017.8090324.

[6] E. Rombaut and M.-A. Guerry, ‘‘Predicting voluntary turnover through human resources database analysis,’’ Manage. Res. Rev., vol. 41, no. 1, pp. 96–112, Jan. 2018, doi: 10.1108/mrr-04-2017-0098.

[7] I. Setiawan, S. Suprihanto, A. C. Nugraha, and J. Hutahaean, ‘‘HR analytics: Employee attrition analysis using logistic regression,’’ IOP Conf. Ser., Mater. Sci. Eng., vol. 830, no. 3, Apr. 2020, Art. no. 032001, doi: 10.1088/1757-899x/830/3/032001.

[8] S. Najafi-zangeneh, N. Shams-Gharneh, A. Arjomandi-Nezhad, and S. H. Zolfani, ‘‘An improved machine learning-based employees attrition prediction framework with emphasis on

feature selection,'' Mathematics, vol. 9, no. 11, p. 1226, May 2021.

[9] F. Fallucchi, M. Coladangelo, R. Giuliano, and E. W. De Luca, ''Predicting employee attrition using machine learning techniques,'' Computers, vol. 9, no. 4, p. 86, Nov. 2020, doi: 10.3390/computers9040086.

[10] S. C. Thompson, A. J. Holmgren, and E. W. Ford, ''Information system use antecedents of nursing employee turnover in a hospital setting,'' Health Care Manage. Rev., v., vol. 47, no. 1, pp. 78–85, 2022, doi: 10.1097/hmr.0000000000000308.

[11] N. El-Rayes, M. Fang, M. Smith, and S. M. Taylor, ''Predicting employee attrition using tree-based models,'' Int. J. Organizational Anal., vol. 28, no. 6, pp. 1273–1291, Mar. 2020, doi: 10.1108/ijoa-10-2019-1903.

[12] K. Naz, I. F. Siddiqui, J. Koo, M. A. Khan, and N. M. F. Qureshi, ''Predictive modeling of employee churn analysis for IoT-enabled software industry,'' Appl. Sci., vol. 12, no. 20, p. 10495, Oct. 2022, doi: 10.3390/app122010495.

[13] I. G. Kang, B. Croft, and B. A. Bichelmeyer, ''Predictors of turnover intention in U.S. federal government workforce: Machine learning evidence that perceived comprehensive HR practices predict turnover intention,'' Public Personnel Manage., vol. 50, no. 4, pp. 538–558, Dec. 2021, doi: 10.1177/0091026020977562.

[14] W. Bao, J. Yue, and Y. Rao, ''A deep learning framework for financial time series using stacked autoencoders and long-short term memory,'' PLoS ONE, vol. 12, no. 7, Jul. 2017, Art. no. e0180944, doi: 10.1371/journal.pone.0180944.

[15] A. Alamsyah and N. Salma, ''A comparative study of employee churn prediction model,'' in Proc. 4th Int. Conf. Sci. Technol. (ICST), Aug. 2018, pp. 1–4, doi: 10.1109/ICSTC.2018.8528586.

[16] D. S. Sisodia, N. K. Reddy, and S. Bhandari, ''Performance evaluation of class balancing techniques for credit card fraud detection,'' in Proc. IEEE Int. Conf. Power, Control, Signals Instrum. Eng. (ICPC