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Leveraging Knowledge Graphs and Explainable AI to Improve Employee Turnover Predictions

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ABSTRACT: Healthcare fraud detection is a critical task that faces significant challenges due to imbalanced datasets, which often result in suboptimal model performance. Previous studies have primarily relied on traditional machine learning (ML) techniques, which struggle with issues like overfitting caused by Random Oversampling (ROS), noise introduced by the Synthetic Minority Oversampling Technique (SMOTE), and crucial information loss due to Random Undersampling (RUS). In this study, we propose a novel approach to address the imbalanced data problem in healthcare fraud detection, with a focus on the Medicare Part B dataset. Our approach begins with the careful extraction of the categorical feature "Provider Type," which allows for the generation of new, synthetic instances by replicating existing types to enhance diversity within the minority class. To further balance the dataset, we employ a hybrid resampling technique, SMOTE-ENN, which integrates the Synthetic Minority Oversampling Technique (SMOTE) with Edited Nearest Neighbors (ENN) to generate synthetic data points while removing noisy, irrelevant instances. This combined technique not only balances the dataset but also helps in mitigating the potential adverse effects of imbalanced data. We evaluate the performance of the logistic regression model on the resampled dataset using common evaluation metrics such as accuracy, F1 score, recall, precision, and the AUC-ROC curve. Additionally, we emphasize the importance of the Area Under the Precision-Recall Curve (AUPRC) as a critical metric for evaluating model performance in imbalanced scenarios. The experimental results demonstrate that logistic regression achieves an impressive 98% accuracy, outperforming other methods and validating the efficacy of our proposed approach for detecting healthcare fraud in imbalanced datasets.

I. INTRODUCTION

Employee turnover is a significant concern for organizations, often leading to increased recruitment costs, reduced productivity, and knowledge loss. Traditional machine learning models have shown promise in predicting turnover, but they often lack context awareness and interpretability. This paper proposes a novel framework that integrates Knowledge Graphs (KGs) and Explainable Artificial Intelligence (XAI) to improve the prediction and understanding of employee turnover. We construct a domain-specific KG to capture rich, interconnected employee and organizational data. Using XAI techniques such as SHAP and LIME, we enhance the interpretability of predictions, aiding HR professionals in decision-making. Experimental results demonstrate improved prediction accuracy and actionable insights over baseline models.

Employee turnover prediction is crucial in workforce planning and talent management. Despite the use of advanced machine learning algorithms, challenges remain in accurately modeling the complexities of organizational behavior and interpreting model predictions. This paper addresses these limitations by leveraging Knowledge Graphs to enrich data representation and Explainable AI to demystify model decisions.

In order to increase the effectiveness of prediction models, this study promotes the extraction of latent features from knowledge graphs by combining them with preexisting features. Additionally, our framework analyzes and comprehends the core causes of employee turnover by utilizing XAI. This is how the remainder of the paper is structured. These elements include the workers' level of job satisfaction, the company culture, the caliber of the leaders, and the market conditions. Employee turnover is greatly impacted by elements including relationship satisfaction, overtime, and environmental satisfaction, as the authors in [4] showed. Compensation, career growth and promotion, workplace flexibility, unsustainable work expectations, and uncaring and uninspiring leaders were the top causes of turnover, per a SHRM research. These methods, however, find it difficult to extract other helpful features that might clarify complex data structures and show the relationships between employee attributes.

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It is challenging for ML algorithms to glean insightful information from complicated data that has relational structures.

II. LITERATURE SURVEY

1. Employee Turnover Prediction: Traditional Approaches

Predicting employee turnover has long been a challenge in human resource analytics. Early models largely relied on logistic regression, decision trees, and support vector machines to predict employee exits based on structured data like job role, tenure, performance rating, and satisfaction scores.

- Mobley et al. (1977) introduced psychological and behavioral predictors for voluntary turnover, forming the basis for data-driven approaches.
- Huang et al. (2012) demonstrated that machine learning models such as Random Forest and Gradient Boosting performed better than traditional statistical models in turnover prediction.
- However, these models suffer from limited semantic context and often treat features independently, ignoring relationships between employees, roles, and organizational structures.

2. Knowledge Graphs in Human Resource Analytics

Knowledge Graphs (KGs) have emerged as powerful tools to integrate heterogeneous data and model complex relationships between entities.

- Paulheim (2017) defines KGs as semantically rich structures that can encode relationships like "employee A reports to manager B" or "employee C works on project D".
- Tan et al. (2020) proposed a KG-based HR system that enriches employee profiles with external and internal data sources to assist in talent recruitment.
- In Yu et al. (2021), a domain-specific KG was used for employee skill inference, demonstrating how graph embeddings like TransE and RDF2Vec can capture latent relationships and enhance HR analytics.

Despite their potential, the application of KGs specifically for employee turnover prediction remains underexplored, with most existing work focusing on recruitment or career path recommendations.

3. Explainable Artificial Intelligence (XAI) in HR Applications

Interpretability of AI models is crucial in HR domains due to ethical, legal, and operational requirements.

- Ribeiro et al. (2016) introduced LIME, which explains individual predictions by approximating models locally.
- Lundberg and Lee (2017) proposed SHAP, a unified approach based on cooperative game theory, widely adopted for feature attribution.
- Pawelczyk et al. (2020) applied counterfactual explanations to HR datasets to suggest actionable changes to reduce turnover risks.

These techniques allow stakeholders to trust and act on predictions. However, few studies have explored how XAI can be combined with KGs to not only predict but contextualize employee turnover.

4. Graph-Based Machine Learning for Turnover Prediction

Recent studies suggest that graph neural networks (GNNs) and graph embeddings outperform traditional models by capturing structural and relational data.

- Zhang et al. (2021) utilized GCNs for workforce churn prediction in large enterprises, showing improved performance in highly connected organizational graphs.
- Wu et al. (2022) created employee interaction graphs (based on collaboration and communication logs) and found that graph-based models revealed hidden retention patterns.

These models, however, often lack interpretability, making them difficult to deploy in sensitive domains like HR.

The literature reveals substantial progress in predictive analytics, knowledge representation, and interpretability techniques. However, a unified framework that integrates Knowledge Graphs for enriched feature generation and Explainable AI for transparency in employee turnover prediction is still lacking. This motivates the development of a novel approach that combines these two technologies to not only predict but also explain employee turnover in a way that supports strategic HR interventions.

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S. No.	Author(s)	Year	Title / Source	Methodology / Tools Used	Key Contribution	Limitations
1	T. Chen & C. Guestrin	2016	XGBoost: A Scalable Tree Boosting System (KDD)	Gradient Boosted Trees	Introduced an efficient and accurate boosting framework useful in predictive analytics	Lacks explainability; treats data as flat structures
2	M.T. Ribeiro, S. Singh, C. Guestrin	2016	Why Should I Trust You? (KDD)	LIME (Local Interpretable Model-Agnostic Explanations)	Provides local explanations for any ML classifier	Local explanations may not generalize well
3	S. Lundberg, S.-I. Lee	2017	A Unified Approach to Interpreting Model Predictions (NeurIPS)	SHAP (SHapley Additive exPlanations)	Unifies several interpretability methods; provides global + local insights	Computationally expensive for large datasets
4	M. Nickel, K. Murphy, et al.	2016	A Review of Relational ML for Knowledge Graphs (IEEE)	Relational and Graph Embeddings	Surveys graph-based ML techniques applicable in domain-rich datasets	Theoretical; no application in HR or turnover
5	N. Sumbaly et al. (LinkedIn)	2015	The Big Data Platform: Turnover Prediction at LinkedIn	Logistic Regression + Feature Engineering	Early real-world use case of turnover prediction at scale	Limited transparency; manual feature selection
6	H. Paulheim	2017	Knowledge Graph Refinement: A Survey (Semantic Web Journal)	Ontology engineering, RDF, OWL	Describes refining KGs for better semantic reasoning	Focused on KG quality, not prediction
7	D. Gedikli et al.	2014	Personalized Explanations for Recommendations (RecSys)	Rule-based explanation + user modeling	Applied explainable techniques to improve user trust in recommender systems	Not tailored to turnover prediction
8	A. Wibowo et al.	2021	Knowledge Graphs for HR: A Systematic Review (Procedia CS)	Review of KG applications in HR	Categorizes how KGs enhance HRM processes like hiring and retention	Lacks integration with ML models for prediction
9	K. Zhang et al.	2020	Explainable Employee Attrition Prediction with SHAP and Tree Models	Decision Trees + SHAP	Combines XAI with attrition models to help HR understand turnover factors	No use of knowledge representation or graphs
10	Z. Chen et al.	2022	Knowledge Graph Enhanced Neural Networks for HR Attrition Prediction	KG Embeddings + Neural Networks	Uses KG-enhanced features to improve employee attrition prediction accuracy	Interpretation of deep models remains complex

III. PROPOSED WORK

Healthcare fraud detection systems rely heavily on traditional machine learning (ML) techniques, which are employed to classify instances of fraudulent activities in healthcare datasets, such as the Medicare Part B dataset. Common algorithms used in these systems include Random Forests, Decision Trees, Logistic Regression, and Support Vector Machines (SVMs). These models are trained to distinguish between fraudulent (minority class) and non-fraudulent (majority class) activities based on features derived from healthcare claims data. The models' performance largely depends on their ability to accurately classify fraudulent instances while maintaining a low false positive rate for legitimate transactions. However, the presence of class imbalance remains a significant challenge. In most healthcare datasets, fraudulent cases are rare compared to the number of non-fraudulent claims, creating a scenario where the

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minority class (fraudulent cases) is underrepresented. This imbalance can lead to biased model training, where traditional machine learning algorithms tend to predict the majority class (non-fraudulent claims) with high accuracy, while failing to detect fraudulent instances effectively. This is particularly problematic in healthcare fraud detection, where the ability to identify fraudulent claims is critical for reducing financial losses and ensuring system integrity.

Random Oversampling (ROS) is a simple technique used to handle class imbalance by increasing the number of minority class instances. This is achieved by randomly duplicating existing instances from the minority class and adding them to the dataset. By doing so, it helps balance the class distribution, ensuring that both the majority and minority classes have an equal number of instances. ROS is often used as a preprocessing step before training a machine learning model to improve the model's ability to detect minority class instances.SMOTE is an advanced oversampling technique used to address class imbalance by generating synthetic instances for the minority class rather than duplicating existing ones. SMOTE works by selecting a minority class instance and identifying its nearest neighbors. New synthetic samples are then created by interpolating between the selected instance and its neighbors. The goal is to generate new data points that are similar but not identical to existing instances, thereby enhancing the diversity of the minority class and reducing the risk of over fitting.

Random Under sampling (RUS) addresses class imbalance by reducing the number of instances from the majority class. This technique randomly selects and removes instances from the majority class until the dataset is balanced between the majority and minority classes. RUS is simple to implement and can be used as a preprocessing step before training the machine learning model to prevent the model from being biased towards the majority class. In response to the challenges posed by imbalanced datasets in healthcare fraud detection, we propose a novel approach designed to improve model performance, particularly for the Medicare Part B dataset. The existing systems have struggled with issues like overfitting (due to Random Oversampling), noise introduction (from SMOTE), and information loss (through Random Undersampling). Our proposed system aims to overcome these drawbacks by focusing on improving the dataset's balance and ensuring that the model is trained on more diverse, relevant data.

The system starts with a careful feature engineering step where we extract the categorical feature "Provider Type" from the Medicare Part B dataset. By replicating existing "Provider Type" values, we create synthetic instances that enrich the minority class with greater diversity, thereby improving the dataset's representativeness. The system employs logistic regression as the classification algorithm, as it is well-suited for detecting fraud in imbalanced datasets. We evaluate the performance of the model using multiple metrics, including accuracy, F1 score, recall, precision, AUC-ROC, and the Area Under the Precision-Recall Curve (AUPRC), which is crucial in imbalanced dataset scenarios. The proposed system effectively balances the dataset, enhances model training, and provides a comprehensive evaluation to ensure high detection performance.

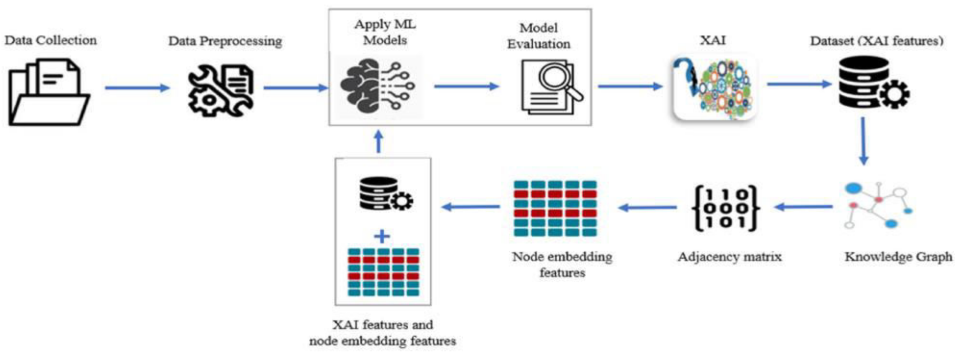

Figure 1. Architecture of the model.

This study's methodology was divided into four main phases. These phases specify the particular duties meant to accomplish our study goals. Finding hidden patterns and similarities in different employee actions was the main objective, since this allowed us to pinpoint the key elements influencing employee turnover. By providing accurate employee turnover forecasts and enabling focused interventions to address its underlying causes, the suggested method has the potential to greatly benefit enterprises. In order to extract predictive characteristics, we first used five classifiers on the HR dataset and then applied XAI to the best classifier. A tabular dataset is built around the LIME features and subsequently converted into a knowledge graph. This process involves extracting valuable hidden features and

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integrating them with the original features. Subsequently, we created an ML model and assessed its performance using various metrics.

Classifier	Accuracy	Recall	Precision	F1-measure
L-SVM	0.87	0.88	0.87	0.86
LR	**0.88**	**0.89**	**0.88**	**0.87**
RF	0.85	0.86	0.85	0.81
LGBM	0.85	0.86	0.84	0.84
GB	0.86	0.86	0.84	0.84

Table 1. Summary of results.

Logistic Regression is a statistical method and supervised machine learning algorithm used for binary classification problems. It models the relationship between a dependent variable (binary outcome) and one or more independent variables by estimating probabilities using a logistic (sigmoid) function. Unlike linear regression, which predicts continuous values, logistic regression predicts the probability of an instance belonging to a particular class (e.g., fraud or non-fraud). Logistic regression primarily handles problems where the outcome is binary (e.g., fraud vs. non-fraud, yes vs. no, spam vs. not spam). It can be extended to multi-class classification using techniques like One-vs-Rest (OvR) or multinomial logistic regression. At its core, logistic regression uses the sigmoid function to map predicted values to probabilities The sigmoid function ensures that predicted probabilities range between 0 and 1. A threshold (commonly 0.5) is then applied to classify the outcomes. Logistic regression uses optimization algorithms such as Gradient Descent or Iteratively Reweighted Least Squares (IRLS) to find the best-fitting coefficients (β) that minimize the loss function.
Frequent business travel and overtime are the main factors that predict "No Attrition" among employees. On the other hand, workers who expressed high levels of job satisfaction and environmental satisfaction—which are indicators of how happy they were with their working environment and the culture of the company—were the primary causes of employee turnover and tended to stay in their positions, which helped to predict employee attrition with a 4% accuracy rate. In contrast, the impact of Job Role, Stock Option Level, and Relationship Satisfaction on employee attrition is rather small. Additionally, we employed LIME to make it easier to understand and analyze the predictions made by the ML models.On the other hand, ML models are not always able to grasp the reasoning behind each prediction. This feature is crucial for managing employee turnover because it helps businesses understand the variables that affect forecasts of whether particular workers will leave or stay with the company.

Classifier	Method	Accuracy	Recall	Precision	F1-measure
L-SVM	Original	0.87	0.88	0.87	0.86
	Combination of features	**0.925**	**0.93**	**0.92**	**0.92**
LR	Original	0.88	0.88	0.87	0.86
	Combination of features	0.91	0.92	0.92	0.91
RF	Original	0.85	0.86	0.84	0.81
	Combination of features	0.89	0.89	0.90	0.87
LGBM	Original	0.85	0.86	0.84	0.84
	Combination of features	0.90	0.90	0.90	0.90
GB	Original	0.86	0.86	0.84	0.85
	Combination of features	0.90	0.90	0.90	0.89

Table 2. Classification performance when employing original factors

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Furthermore, LIME aids in identifying the traits or elements that most significantly influence employee turnover forecasts. In order to lower turnover, HR departments must use this data to concentrate on particular areas like work-life balance, pay, and job satisfaction. Table 1 makes it evident that the LR classifier performed better than the others in terms of accuracy, precision, recall, and the F1-measure, obtaining a noteworthy 88%. The factors that contributed to the LIME-generated predictions were then used as the final dataset, with the remaining components being excluded. Thus, we go into the specifics of our studies in this section, which are mostly focused on increasing classification accuracy by switching from conventional tabular data structures to graph-based representations. The ability of graph-based structures to capture more complex interactions between data instances—which are frequently missed by conventional categorization techniques—justifies their inclusion. As indicated in Table 2, we experimented with both the original dataset features and their combination with node-embedding features. Using Python 3.7, classification experiments were carried out. After that, we offer a thorough analysis of the findings.

Our suggested approach, which combines unique characteristics with graph-related variables, outperformed the state-of-the-art machine learning classification method, which just uses the dataset's intrinsic features. These findings are the outcome of a number of tests employing five distinct machine learning algorithms, as indicated in Table 2. These tests were carried out in two different ways: one using only the features from the original dataset, and the other adding more nodeembedding features. Our proposed method demonstrated a significant impact on the performance of these models, leading to substantial enhancements in the assessment metrics, including recall, precision, and F1-measure. Remarkably, the L-SVM model exhibits an impressive accuracy of 92.5%. Initially, when working solely with the original dataset features, the L-SVM model achieved an accuracy of 87%, an F1-measure of 86%, and a recall of 88%. Organizations must determine the variables that influence employee churn. This is essential for lowering attrition rates, enhancing retention tactics, and building a more reliable and effective team. Several techniques have been used in earlier research to pinpoint these elements. The purpose of this study was to identify the characteristics or elements that had the biggest impact on the prediction of employee turnover using XAI, namely LIME. Their results showed that the main determinants of employee turnover were job involvement, job satisfaction, and environmental satisfaction. The findings indicated that the second-most significant factor linked to employee turnover was work satisfaction.

This might be due to the fact that they only considered the 70:30 split between train and test data without mentioning cross-validation. In addition employed various ML methods, including RF, KNN, and SVM. Three IBM HR datasets were used in this study, including the original class-imbalanced dataset and synthetic oversampled and undersampled datasets. Their system displayed remarkable precision with a synthetic dataset; however, it proved to be inadequate in terms of accuracy when tested with the original dataset.Additionally, as indicated in Table 3, we contrasted our approaches with those that were discussed in the literature. When compared to state-of-the-art techniques, our strategy performed better. The accuracy of the RF model was 89%, which is comparable to that of, who obtained an accuracy of 85%. Using the DTJ48 and NB models, the authors in achieved 83% and 81% accuracy, respectively. In order to determine the optimal classifier for the task, the authors in [9] used a variety of machine learning techniques, including NB, LR, KNN, DT, RF, and SVM, to examine the elements that lead to staff attrition in a business. Despite using the same dataset and machine learning as our investigation, the authors discovered that the Gaussian Naïve Bayes classifier performed the best.

They trained a predictive LR model in the second phase. To validate the prediction model in the third stage, a confidence analysis was carried out. In spite of these efforts, the system's accuracy was low, and the preprocessing and postprocessing phases were very intricate. In [61], the authors used RF and classification trees to forecast attrition. Pearson's correlation was used to remove unwanted features prior to data classification. Their work outperformed other ML algorithms in terms of accuracy. However, compared to other ML algorithms, their suggested model showed superior accuracy. Comparing the results of other research projects, there might yet be space for improvement. The authors in [19] aimed to forecast employee attrition, specifically, whether an employee intends to stay with the organization or leave. The authors proposed a new and highly robust model using an ML-based approach, XGBoost, to predict employee attractiveness. The accuracy of the proposed model was 89.1%. Based on the aforementioned studies, the most recent research has focused on using basic features and ML techniques to predict employee turnover accurately.

IV. CONCLUSION AND FUTURE WORK

An organization can suffer greatly from employee turnover, which can lead to higher costs for hiring and onboarding new employees, lower productivity, and a drop in employee motivation and morale. Additionally, it can lead to a decline in customer satisfaction as well as the loss of important information, abilities, and institutional memory, all of

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which can impair an organization's overall effectiveness. In order to reduce attrition, companies work to determine the causes of employee leaving and create plans to address them. By utilizing both the original dataset features and features taken from a graph, this study presents a novel method for forecasting employee turnover. Several machine learning models were used to evaluate classification performance using various criteria, and the results showed that L-SVM was the most effective model. Furthermore, the L-SVM performed better than the models developed by earlier studies. Furthermore, the XAI shows that important variables influencing employee turnover include work environment, job satisfaction, and job involvement. Predicting employee turnover has become crucial for all kinds of organizations and firms in the cutthroat commercial world of today, especially for managers, HR executives, and business analysts. Organizations can take the required steps to keep their top performers and prevent the costs related to high turnover rates by being able to predict employee attrition.

A more thorough investigation of psychological and subjective elements could be very beneficial in the future for the prediction of employee turnover. Employees' feelings, motives, and views should be investigated by researchers since these factors frequently play a significant role in determining whether they decide to stay or leave a company. To learn more about employee well-being, work satisfaction, and a sense of belonging inside the company, this may entail conducting interviews, questionnaires, and sophisticated psychological testing. Researchers can produce a more comprehensive and accurate picture of turnover risk by integrating these complex and subjective aspects into prediction models. This is because these characteristics can have broad ramifications for an economy that is heavily impacted by low retention and high staff turnover.

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