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RESEARCH ARTICLE

Enhancing the Prediction of Employee Turnover With Knowledge Graphs and Explainable AI

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ABSTRACT Employee turnover poses a critical challenge that affects many organizations globally. Although advanced machine learning algorithms offer promising solutions for predicting turnover, their effectiveness in real-world scenarios is often limited because of their inability to fully utilize the relational structure within tabulated employee data. To address this gap, this study introduces a promising framework that converts traditional tabular employee data into a knowledge graph structure, harnessing the power of Graph Convolutional Networks (GCN) for more nuanced feature extraction. The proposed methodology extends beyond prediction and incorporates explainable artificial intelligence (XAI) techniques to unearth the pivotal factors influencing an employee's decision to either remain with or depart from a particular organization. The empirical analysis was conducted using a comprehensive dataset from IBM that includes the records of 1,470 employees. We benchmarked the performance against five prevalent machine learning models and observed that our enhanced linear Support Vector Machine (L-SVM) model, combined with knowledge-graph-based features, achieved an impressive accuracy of 0.925. Moreover, the successful integration of XAI techniques for attribute evaluation sheds light on the significant impact of job environment, job satisfaction, and job involvement on turnover intentions. This study not only furthers the development of advanced predictive models for employee turnover but also provides organizations with actionable insights to strategically address and reduce turnover rates.

INDEX TERMS Employee turnover prediction, machine learning, explainable AI, knowledge graph.

I. INTRODUCTION

In today's dynamic and competitive business environment, retaining valuable human capital is an insurmountable challenge for organizations. Employee attrition, defined as an employee's voluntary or involuntary departure from an organization, has emerged as a significant concern for businesses in all sectors. High employee attrition affects an organization's morale, productivity, and overall success. This underscores the importance of conducting a thorough analysis of this critical issue [1]. This has resulted in significant financial losses. Research by the Society for Human Resource Management (SHRM) suggests that replacement costs range from 50% to 60%, with total costs ranging from 90% to 200% [2]. Gallup reports that replacing employees can cost up to 150% of their annual salary, and a Deloitte study indicates that the cost of losing a single employee can vary from tens of thousands to 1.5 to 2 times their yearly salary [3]. Employee turnover is affected by many complicated factors that interact differently in organizations. These factors include the employees themselves, how satisfied they are with their jobs, the organization's culture, how good the leaders are, and the state of the market. The authors in [4] demonstrated that factors such as relationship satisfaction, overtime, and environmental satisfaction significantly impact employee turnover. According to a study conducted by the SHRM, the top reasons for turnover were compensation, career development and advancement, workplace flexibility, unsustainable work expectations, and uncaring and uninspiring leaders [5]. Employee turnover is primarily influenced by factors such as

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job level, income, wages, and age [6]. Consequently, HR professionals, managers, and organizational leaders who wish to maintain stability and development must understand the key factors that contribute to and predict employee turnover. Accordingly, academic circles have attempted to predict employee turnover. Recently, a data mining method was used to build machine learning (ML) models to forecast employee turnover [4], [6], [7], [8]. However, most existing research has utilized single ML models, such as SVMs, logistic regression (LR), naïve Bayesian (NB), decision trees (DT), and random forests (RF). Most studies have focused primarily on using basic features and ML techniques to predict employee turnover with reasonable accuracy [7], [8], [9], [10]. However, these approaches struggle to extract additional useful features that can help us understand complex data structures and reflect the connections among employee features. ML algorithms face difficulties extracting valuable insights from complex data containing relational structures [11].

This study advocates the extraction of latent features from knowledge graphs by integrating them with existing features to bolster the efficacy of predictive models. Furthermore, our framework harnesses the XAI to dissect and understand the fundamental factors that drive employee turnover. The remainder of this paper is organized as follows. Section II offers a comprehensive review of the relevant literature. Section III describes the methodology employed in the proposed framework. Section IV presents an exposition of the findings and an in-depth discussion of their implications. The paper concludes with Section V, which not only provides a summary of the research but also explores avenues for future scholarly inquiries.

II. RELATED WORK

Recently, staff attrition has attracted significant interest from professionals in human resources, management teams, and research. The consequences of high turnover rates can be far-reaching, including increased recruitment and training costs, decreased team cohesion, loss of institutional knowledge, and potential disruptions to workflow [1], [2], [3]. Consequently, the existing literature has proposed and utilized several ML algorithms to predict employee turnover. In this section, we explore and discuss the most relevant ML techniques applied to employee turnover.

Two studies conducted by the authors in [4] and [5] investigated various ML models for predicting employee churn, including DT, Naïve Bayes (NB), Support Vector Machine (SVM), Neural Network (NN) models, K-Nearest Neighbors (KNN), and RF. Both studies identified SVM as the top-performing method for predicting employee turnover, demonstrating its high accuracy and reliability in churn prediction tasksOther researchers have focused on predicting employee turnover using LR. For instance, the authors in [6] investigated the accuracy of a real-world dataset from a Belgian private company's HR system in predicting turnover using an LR model. The area under the receiver operating characteristic curve (AUC) value obtained was 0.7432. In addition, the authors in [7] explored staff turnover using LR and identified 11 key determinants. The LR model achieved 75% accuracy, 73% sensitivity, and 75% specificity when observing approximately 4,000 employees over 261 days in 2015. Furthermore, the authors in [8] presented a method to employ LR to forecast employee departures. They introduced the "max-out" method to reduce the feature space dimension and then trained the logistic model for prediction. By comparing their proposed feature-selection method with other methods, they concluded that it was a superior predictor.

In a previous study conducted by [9], several ML algorithms were comprehensively analyzed. These techniques include linear Support Vector Machine (L-SVM), LR, SVM, KNN, RF, DT, and NB for multivariate Bernoulli models, and Gaussian NB. Methods for predicting employee retention include Gaussian naïve Bayes, naïve Bayes for multivariate Bernoulli models, LR, KNN, DTs, RFs, SVM, and L-SVM. The Gaussian NB classifier yielded the most favorable outcomes for this dataset, demonstrating the highest recall rate (0.54) and maintaining a low false negative rate (4.5%) across the observation set. Similarly, the authors in [10] focused on nurses' utilization of electronic medical records and their potential relationship to voluntary turnover. They employed the NB algorithm, which achieved an accuracy of 73.4% in predicting nurse turnover and 84.1% in predicting non-turnover instances.

The authors in [11] introduced a binary classification model based on the DT algorithm that predicts the probability of employee turnover by considering management factors and organizational culture. They applied the gradient boosting (GB), RF, and DT algorithms to evaluate a dataset consisting of anonymous resumes gathered from the Glassdoor website. Their study revealed that the RF and DT models were the most effective for predicting attrition. Meanwhile, the authors in [12] introduced a prediction model that utilizes the chi-squared approach. This model effectively classified employee turnover and achieved a remarkable accuracy of 98% using the DT algorithm. The NN and RF algorithms were equally ranked as the second-best performers at 97%. The LR and SVM exhibited comparatively lower levels of accuracy. In [13], a research endeavor to identify the crucial factors influencing turnover intention among US Federal employees and to classify high-risk subgroups susceptible turnover. The authors employed Classification and Regression Trees (CART) and supplemented their analysis with extreme gradient boosting trees (GBDTs). Notably, the results highlighted CART as the top-performing model, displaying F1-measure, recall, and precision values of 0.82, 0.86, and 0.79, respectively. Additionally, the CART method exhibited an accuracy of 74.96% and an AUC of 0.72.

Several studies have emphasized the use of RF as a powerful approach for predicting employee turnover and attrition. The authors in [14], investigated the viability of predicting turnover among software developers. This study utilized algorithms such as NB, SVM, DT, KNN, and RF. Similarly, [15] identified the most effective approach for predicting employee turnover using RF, DT, and NB. They evaluated the performance of the models using the HRIS data from a prominent Indonesian telecommunications company from 2015 to 2017. In another study by [16], five ML algorithms were employed to forecast staff turnover: NB, RF, DT C5.0, KNN, and L-SVM. Additionally, [17] used various ML algorithms, including SVM, DT, and RF, to forecast employee turnover. Across all these studies, RF consistently outperformed the other algorithms. In their study, [18] proposed a model to predict individual truck driver turnover incidents using SVM, RF, and LR. In both experiments and across the three classifiers, these models demonstrated an accuracy range of 60–70% and a sensitivity level of 50–60%. Additionally, the authors highlighted that the predominant factors explaining the predictive power of the models were the consistency and quantity of weekday driving assignments.

Several researchers have demonstrated that boosting algorithms consistently outperform ML algorithms in predicting employee turnover. In addition, the authors in [3] compared XGBoost with various ML algorithms, including SVM, LDA, KNN, RF, NB, and LR, using data from retailers' worldwide HRIS and the Bureau of Labor Statistics. The results indicated that XGBoost demonstrated superior performance, exhibiting higher accuracy, lower runtime, and efficient memory usage. In [19], the XGBoost algorithm was used to forecast staff attrition and intentions to resign from an organization, achieving an error rate below 30% and an accuracy of approximately 90%. Meanwhile, [20] examined the effectiveness of ML techniques using two datasets: one from a regional bank in the US and another synthetic dataset from IBM Watson Analytics. Among the ten methods evaluated in this comparative analysis, XGBoost demonstrated the highest overall performance in terms of accuracy, precision, recall, F1-measure, and AUC. In addition, [21] introduced an ECPR scheme that utilizes multi-attribute decision-making and the CatBoost algorithm. Their study categorized employees using the AEIM and employed CatBoost for class-based employee turnover prediction. The ECPR scheme outperformed the other ML algorithms in predicting turnover.

Furthermore, the authors in [22] introduced a proactive talent management model to predict employee turnover, departing from the traditional ex-post approach. To achieve this, various ML algorithms were employed, such as SVM, artificial NN (ANN), LR, XGBoost, RF, and ensemble models. To address imbalanced data, they utilized the synthetic minority oversampling technique (SMOTE). The study outcomes indicated that the ensemble model, comprising ANN and RF as the base algorithms and LR as the meta-learner, demonstrated the most effective performance.

Moreover, [23] performed an investigation employing various ML techniques such as NN, DT, RF, and LR. Their findings revealed that the LR model exhibited superior performance compared to other models in predicting employee turnover.

The authors in [24] utilized an NN algorithm to forecast employee turnover. By leveraging historical employee information, they utilized ML algorithms and data visualization tools to discern the factors contributing to employee departure and pinpoint individuals most likely to leave in the future. The ANN algorithm yielded 164 accurate predictions, with an accuracy rate of 40%. When extrapolated to the present workforce, the model suggested that 20% of the workforce was at high risk of leaving, whereas 49% was susceptible to leaving in the mid-term future. By contrast, 31% of employees were considered likely to remain in the long term. The authors in [25] proposed an ensemble learning model for predicting employees' intentions to quit. They considered features such as networking site activities, profile updates on job portals, job participation, and organizational commitment. In addition, the authors employed several classification algorithms, including GB, KNN, NB, SVM, GB, LR, RF, NN, and ensemble learning. They found that the most successful ensemble learning model was achieved by integrating GB, LR, and KNN. Furthermore, the three predictors that made the most significant contributions to predicting both intention to quit and non-intention to quit were job involvement, updates of profiles on job portals, activities on professional networking sites, and updates of profiles on job portals.

In addition, the authors in [26]utilized SMOTE to tackle class imbalance issues in the 2018 National Sample Survey of Registered Nurses dataset to correctly predict employee turnover, and applied ML algorithms, including LR, RF, XGBoost, and DT. Their findings indicated that SMOTE_RF and SMOTE_ XGBoost stood out as the optimal models, achieving accuracy scores of 74.39% and 73.88%, respectively. Furthermore, the authors in [27] introduced deep NNs to predict employee turnover and tested their model on an imbalanced IBM Analytics dataset. Their model achieved high performance with 89.11% accuracy, outperforming state-of-the-art ML techniques. In another study by [28], the authors tackled employee attrition by employing various ML techniques. They specifically proposed a feedforward NN called Fresnel cosine integral weights and structure determination. The model accurately classified employee turnover and demonstrated competitiveness and reliability compared with other ML techniques. Overall, these studies highlight the application of ML techniques and their potential effectiveness in predicting employee turnover. More recently, [29] proposed a hybrid GA–DeepAutoencoder–KNN model to predict employee turnover. Their results demonstrated that the proposed model achieved a significantly higher accuracy of approximately 90% compared with other conventional models. In conclusion, the reviewed papers studied employee turnover and aimed to achieve good prediction performance, whereas the majority of these studies adopted supervised ML because of the nature of the available data. Furthermore, a significant proportion of the authors of the reviewed papers did not consider the interconnections or relationships between various entities. Instead, they assumed that the employees in the dataset were unrelated and independent. Based on these observations, the solutions proposed in this research involve the transformation of tabulated data into knowledge graphs. This approach is aimed at effectively capturing structural information from a dataset. Furthermore, the proposed framework utilizes explainable Artificial Intelligence (XAI) to examine the main reasons behind employee turnover.

III. METHODOLOGY

This research adopts the Cross-Industry Standard Process for Data Mining (CRISP-DM) [30], encompassing data collection, model development (including the proposed approach), model evaluation, results presentation, and model deployment. CRISP-DM's versatility lies in its applicability to diverse industries, making it the prevalent choice for data mining projects, that lead to valuable outcomes. The following sections elaborate on each phase in depth.

A. DATA COLLECTION

In this study, we utilized an International Business Machines Corporation (IBM) dataset originally sourced from IBM Watson Analytics in the IBM community. The dataset comprises 1500 observations and 35 features related to job involvement. These features encompass various aspects, including age, education field, education, employee number, employee count, distance from home, department, business travel, job role, job level, job satisfaction, hourly rate, daily rate, monthly rate, monthly income, marital status, gender, satisfaction with the work environment, number of companies worked, relationship satisfaction, over time, performance rating, total working years, stock option level, and training time. The dataset also includes a crucial dependent variable denoted as "Attrition," where "No" represents employees who remained with the organization and "Yes" represents employees who departed. Appendix A provides descriptions of these attributes.

B. DATA PREPROCESSING

Data preprocessing is a crucial aspect of ML that can substantially guide the performance of a model. This study employed data preprocessing techniques, such as cleaning, categorical data encoding, and rescaling, to improve ML models.

1) DATA CLEANING

At this stage, we excluded certain features, such as the number of employees aged over 18 years and standard hours worked, which were found to be uniform for all employees based on the dataset. The number of employee attributes was excluded because their values were not relevant to our objective.

2) DATA ENCODING

Categorical features cannot be used directly in most ML algorithms. The initial dataset contained several categorical variables, including attrition, business travel, department, education field, sex, job role, marital status, overtime worked, and age over 18 years. These attributes need to be transformed into numerical data, which is achieved through the process of one-hot encoding. Initially, we identified unique values and their corresponding numerical representations. Subsequently, each value is assigned a one-hot binary vector.

3) RESCALING

In real-world datasets, most features exhibit variations in terms of range, units, and magnitude. An issue arises when the magnitude of one feature surpasses that of others, resulting in its dominance over the remaining features. Consequently, raw data must be scaled to mitigate the influence of varying quantitative units [31], [32]. Normalization is a common method for rescaling feature values. Therefore, in this study, the MinMaxScaler technique was used to normalize the feature values, thereby enhancing the model's performance, minimizing bias, facilitating the model's interpretation, and serving as a convenient preprocessing stage.

C. MODEL BUILDING

In the modeling process, we selected ML algorithms based on insights derived from the existing literatures [3], [6], [7], [8], [9], [11], [14], [15], [17], and [33]. These ML algorithms were then used to identify the best algorithm for predicting employee turnover. Our primary aim is to train each algorithm on a designated feature set and determine the algorithm that produces the most precise results. Following this determination, the selected algorithm was used for prediction. This study considers the following ML classification algorithms:

1) LINEAR SVM

SVM, initially developed by [34], is a powerful algorithm used for supervised learning. It serves both classification and regression modeling tasks and can handle a wide range of feature types effectively. The algorithm is based on the inductive principle of Structural Risk Minimization from statistical learning theory, which addresses overfitting by striking a balance between model complexity and fitness with respect to the training data [34]. In this study, we focused on employing L-SVM. An essential advantage of the L-SVM is its high tolerance to noisy data, which allows it to handle challenging datasets effectively. Moreover, the hyperplane function in the SVM contributes to its impressive performance and excellent generalization capability in ML classification problems [35].

2) LR

LR stands as a classical algorithm extensively employed for modeling the connection between a dichotomous feature and one or more features [36]. It represents a form of general linear regression, thus resembling multiple linear regressions in various aspects. LR has widespread applications in tackling binary classification problems. Nonetheless, it is adaptable to multi-classification tasks. The LR algorithm can be used to (i) quantify the importance of the relationship between each feature and the binary response feature or (ii) classify instances between two categories. LR is a straightforward parametric statistical approach that utilizes numerical computations to establish a model by identifying the classification parameters that exhibit discriminating abilities for each group, along with the corresponding classification rules. One notable advantage of LR is its ability to operate without making assumptions regarding class distributions in the feature space [37].

3) RF

RF is an ensemble method that combines regression trees or classifications to boost the DT process through multiple voting mechanisms [37]. For example, in a scenario with n samples and m features, the RF mechanism initially identifies a value m that determines the number of features selected by each tree algorithm. It then generates k-tree algorithms by obtaining and using k samples from the dataset and creating k bags of external data for testing purposes. Each tree algorithm independently classifies the samples, and the final classification result is determined based on majority voting, considering the decisions of all algorithms [38].

Ensemble methods are widely recognized for their superior performance when individual members exhibit diversity and incorporate randomness. The RF algorithm achieves this diversity by using two main sources of randomness. First, each tree in the RF is constructed using a different bootstrapped sample from the training data. Second, during the construction of each tree, only a randomly selected subset of the features was considered for each node. RF combines the principles of bagging, where individual models are assembled by sampling with replacement from the training data, using the random subspace approach, where each tree is constructed from a random subset of features [39]. Consequently, this algorithm has gained considerable popularity because of its user-friendly nature and ability to produce easily interpretable results.

4) LGBM

Light gradient-boosting machine (LGBM) is a GB framework that employs a tree-based learning approach. It distinguishes itself from other methods by developing trees in a vertical manner as opposed to horizontal growth. This means that the LGBM grows trees in a leafwise fashion, whereas the alternative approach adopts a level-wise strategy. The leafwise method selects the leaf with the highest delta loss for expansion, resulting in a more significant loss reduction compared to the level-wise algorithm. It has garnered notable efficiency and scalability advantages over previous GBDT implementations. These improvements are achieved through two proposed methods, gradient-based one-side sampling (GOSS) and exclusive feature bundling (EFB), which enhance the performance of existing GBDT implementations.

GOSS is a strategy aimed at reducing the number of data instances considered during the creation of a DT ensemble. This is achieved by retaining only the data instances that contribute significantly to the gradient of the loss function for the ensemble of DTs [40]. The selected reduced set of instances is then utilized in the procedures required to add the next DT to the ensemble. The EFB is an approach that focuses on feature reduction. It leverages the sparsity of feature sets to create a new, smaller feature set that preserves the same information as the original (sparse feature set) [40]. The EFB technique helps to streamline the feature space and enhances the efficiency of the learning process. Notably, the LGBM demonstrates exceptional performance with high training speed owing to its optimized implementation, which significantly reduces training time. Additionally, the algorithm exhibited low memory utilization during both the training and testing phases, thereby efficiently conserving system resources. Furthermore, the LGBM surpasses other boosting algorithms in terms of accuracy and utilization of data and features. Its ability to harness data effectively results in more accurate predictions and superior overall performance compared with competing methods [41]. These findings underscore the practicality and efficacy of the LGBM for a wide range of ML tasks.

5) GB

The concept of GB was proposed by [42]. In ML, boosting has been regarded as one of the most influential concepts introduced in the past three decades [43], with the distinction between binary and continuous response variables; GB functions as a classification or regression model [44]. This approach sequentially assembles the results of several weak learners, typically DTs, to construct a predictive model that is both accurate and resilient [45]. Unlike the commonly used methods for data-driven modeling, which typically involve fitting a single powerful predictive model, the boosting technique combines multiple comparatively less powerful predictive models to create a more robust ensemble estimator. However, other widely used machine learning ensemble techniques, such as RF, rely on explicitly averaging the predictions of predictive models [46]. The core concept underlying GB is training a sequence of weak models on the residuals of previous models, resulting in a gradual reduction in errors through repeated learning. This iterative methodology enables the algorithm to consistently enhance its performance by rectifying the shortcomings of previous models [44]. Owing to this exceptional adaptability, GBMs can be customized for data-driven endeavors. This significantly expands the scope of the model design, thereby reducing the process of determining the optimal loss function for experimentation and refinement. Nevertheless, the implementation of boosting algorithms is relatively straightforward, enabling the exploration of diverse models. Furthermore, not only in practical applications, but also in a variety of machine learning and data mining challenges, GBMs have demonstrated remarkable success [43].

D. MODEL EVALUATION

This study employed both cross-validation and train–test splits to achieve an accurate model evaluation and enhanced generalization performance. The original datasets were partitioned into two sets, training and testing datasets, with the training set accounting for 80% and the testing set for 20% of the original data, following the standard practices for model evaluation. Additionally, a 5-fold cross-validation approach was employed for further assessment.

In accordance with [47] "Evaluation measures have a pivotal role in evaluating classification performance and shaping algorithmic modeling," as diverse metrics can highlight distinct facets of algorithm performance. Hence, this study incorporated multiple performance evaluation metrics such as accuracy, precision, recall, and F1-measure. The evaluation metrics are as follows:

- True Positive (TP): both predicted and actual values are positive.
- True Negative (TN): both predicted and actual values are negative.
- False Positive (FP): When the approach predicts a positive value, the actual value becomes negative. item False Negative (FN): When the approach predicts a negative value, the actual value is positive.

The accuracy is the ratio of correct predictions to the total number of predictions. Precision is the proportion of positive values correctly identified by the model, whereas recall is the proportion of correctly identified TP values. However, the F1-measure gives equal consideration to precision and recall. These measures are defined as follows:

$$Accuracy = (TP + TN)\big/(TP + FP + TN + FN) \quad (1)$$

$$Recall = TP\big/(TP + FN) \quad (2)$$

$$Precision = TP\big/(TP + FP) \quad (3)$$

$$F1 - measure = 2((precision * recall)\big/(precision+recall)) \quad (4)$$

E. INTERPRETABLE MODELS

The demand for transparent ML models has grown significantly owing to the increasing importance of transparency and trust in the decision-making processes of artificial intelligence systems. It is crucial to understand and interpret the rationale behind the decisions made using these models. Interpretability entails comprehending why and how an ML model arrives at a specific conclusion or outcome, offering visual, quantitative, and qualitative explanations of the predictive factors. This interpretive capability is essential for all the ML algorithms. However, the inherent black-box nature of many ML models limits our ability to understand the reasoning behind each prediction [48]. One method that addresses this challenge is the Local Interpretable Model-Agnostic Explainer (LIME), a well-established approach designed to enhance the interpretability of complex ML models [48]. LIME's primary objective is to elucidate how a model achieves a particular prediction for a given instance by approximating the behavior of the model in the vicinity of that instance. This is a versatile tool for handling various types of data and models. LIME accomplishes this by establishing a linear relationship between the generated sample points and a given prediction, thereby illustrating the significance of each feature [49].

LIME is particularly valuable because of its capacity to address the black-box nature of ML models, while simultaneously achieving high accuracy and interpretability in decision-making processes. Moreover, this study aimed to uncover the primary factors contributing to employee attrition within organizations. In this context, LIME is a valuable tool for identifying the precise and significant attributes in a dataset. LIME provides localized explanations for specific rows in a dataset by perturbing data samples and observing their impact on the original data, ultimately demonstrating the importance of each feature in these instances [50].

F. PROPOSED APPROACH

The approach of this study consisted of four key stages. These stages detail the specific tasks aimed at achieving our research objectives. The primary goal was to uncover hidden patterns and similarities within various employee behaviors, enabling us to identify the crucial factors contributing to employee turnover. The proposed solution has the potential to benefit organizations significantly by enabling precise projections of employee turnover and facilitating targeted interventions to address its root causes. First, we employed five classifiers on the HR dataset and applied XAI to the most successful classifier to extract predictive features. The LIME features serve as the foundation for a tabular dataset, which is then transformed into a knowledge graph. This process involves extracting valuable hidden features and integrating them with the original features. Subsequently, we created an ML model and assessed its performance using various metrics. An overview of the proposed methodology is shown in Fig. 1.

1) CALCULATING THE SIMILARITIES

The initial goal of our framework involves investigating potential techniques for transforming tabulated data into a knowledge graph, mirroring approaches already utilized within the domains of education [51] and healthcare [52].

2) ADJACENCY MATRIX

The adjacency matrix is a square matrix that graphically depicts the relationships between nodes. The values assigned to each element in this matrix represent the weights of the edges connecting the nodes. When no edge connects the two nodes, the value of the corresponding matrix element is typically zero. When an edge connects two nodes, the value of the corresponding matrix element is 1. Employees (nodes) with relationships or edges have a value of 1, whereas those without an edge have a value of 0.

3) CONSTRUCTION OF KNOWLEDGE GRAPHS (KG)

Dataset (*D1*), referred to in Section III-A, was converted into a graph. *D1* comprises 1470 employees and 31 factors.

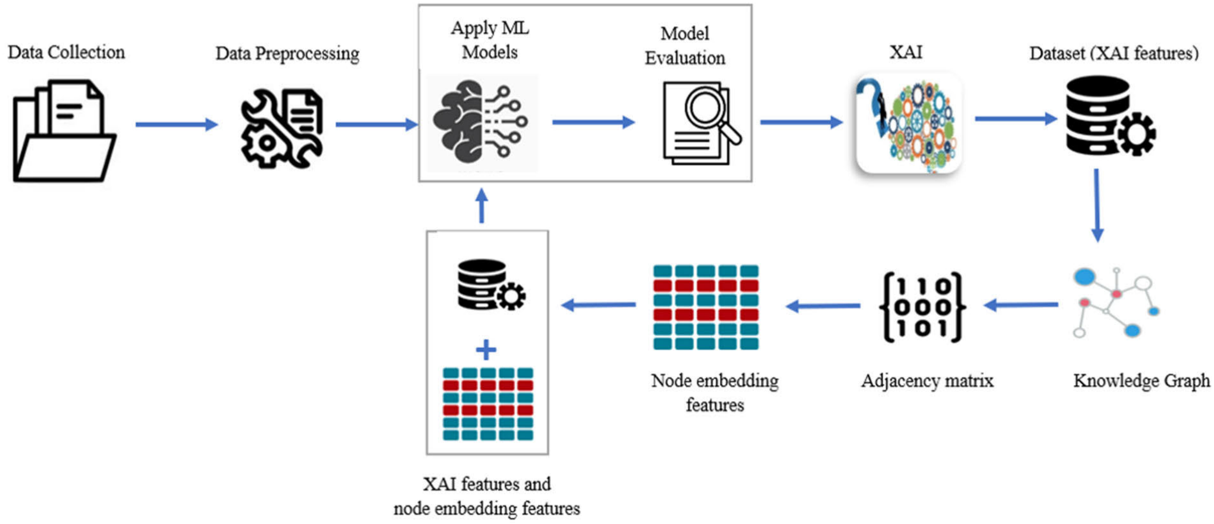

FIGURE 1. **Overview of the proposed methodology.**

The first step is to transform *D1* into graph *G,* with nodes designated as *V* and edges (or links) designated as *E*. Each edge connects to a pair of nodes, which are expressed as follows:

$$G = (V, E) \tag{5}$$

In this approach, every employee is represented by a node, and the relationship between two employees is modeled as an edge. The assumption is that employees who share similar attributes will have stronger edges. A knowledge graph was constructed by identifying the nodes, properties, and edges. Each employee was considered a node, and properties such as age, education, and monthly income were associated with each employee node. For instance, if an employee has features similar to those of another worker, an edge would appear. Upon converting the tabular dataset into a knowledge graph, various nodes were extracted, as described in Section III-C4.

4) NODE EMBEDDING

A node-embedding algorithm is an ML technique that creates vector representations or embeds graph nodes to capture structural information and the relationships between nodes [53]. Node embedding aims to transform nodes into a vector space in which the similarity between nodes can be measured [54]. Several node-embedding techniques, such as GCNs, random walk, and deep walk, can generate node embeddings from knowledge graph data. In this study, a GCN was used as a type of NN that can extract embeddings or features from graph nodes. GCNs operate on a graph structure by aggregating and transforming data from a node's neighborhood to generate a new representation for that node. The input feature vector represents each node in the GCN. The GCN then applies a sequence of convolutional layers to the graph, with each layer aggregating and transforming the features of a node's neighbors to generate a new representation for that node. This procedure can be repeated across multiple layers, enabling the GCN to capture increasingly complex relationships between the graph nodes. The GCN output is a collection of embeddings, each representing a node in a graph [55]. These embeddings can function as features for tasks such as classifying nodes, predicting links, and showing how a graph is combined. A valuable approach involves feature combinations to enhance classification performance. In this context, we augmented the classification performance by integrating node-embedding features with the original feature set. We conducted experiments using both the original factors and a combination of the original features and node embeddings using multiple ML classifiers.

IV. RESULTS AND DISCUSSION

In this section, we describe experiments conducted using the Python programming language. Various classification methods have been employed to construct predictive models. Subsequently, we used XAI techniques to discern the most significant features within the predictive model. We applied multiple algorithms to the dataset, including the L-SVM, LR, RF, LGBM, and GB.

The results achieved by these classifiers are presented in Table 1, demonstrating that LR exhibited superior performance compared to the other classification methods.

Therefore, the XAI technique (LIME) was implemented in LR to elucidate the factors contributing to these predictions. Fig.2 shows the contribution of each factor to attrition (1) and no attrition (0). As shown in Fig.2, the line explanation indicates the contribution of each factor to attrition (1) and no attrition (0). We assessed two sets of results corresponding to Classes 0 and 1 (attrition and no attrition, respectively). The LIME explanation illustrates how the values of each feature impact the prediction, for

TABLE 1. Outcomes of classifiers.

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

instance, whether it signifies "no attrition" or "attrition." In addition, Fig. 2 shows the attributes that contributed to these predictions. The foremost contributors to predicting 'No Attrition' in employees are overtime and frequent business travel. Conversely, employees who reported high job satisfaction and environmental satisfaction, which refer to employees' satisfaction with their working conditions and the organization's culture, were the main factors of employee turnover and tended to remain in their jobs, contributing to a 4% chance of predicting employee attrition. By contrast, Relationship Satisfaction, Stock Option Level, and Job Role have comparatively minor effects on employee attrition. Furthermore, we used LIME to facilitate the interpretation and clarification of the predictions generated by the ML models, as shown in Fig.2. In contrast, ML models have limitations in interpreting the rationale behind each prediction. This capability is of utmost importance in addressing employee turnover, as it enables organizations to comprehend the factors that influence predictions regarding the likelihood of specific employees leaving or remaining with the company. In addition, LIME assists in determining the factors or characteristics that have the most significant impact on employee turnover predictions. This information is essential for HR departments to focus on specific aspects such as job satisfaction, compensation, or work-life balance to reduce turnover. It is clear from Table 1 that the LR classifier outperformed the others with respect to the F1-measure, accuracy, precision, and recall, achieving a notable 88%. Subsequently, the factors contributing to the LIME-generated predictions were employed as the final dataset while excluding the remaining factors. Therefore, in this section, we explore the details of our experiments, which are primarily aimed at improving classification accuracy by shifting from typical tabular data structures to graph-based representations. The rationale for incorporating graph-based structures is their capacity to capture more intricate interrelationships among data instances, which are often overlooked in traditional classification methods. Our experiments were conducted on both the original dataset features and their combination with node-embedding features, as listed in Table 2. Classification experiments were performed using Python 3.7. We then provide an in-depth analysis of the results.

Our proposed method, which combines graph-related attributes with original features, produced noteworthy results, surpassing the performance of the current state-of-the-art ML classification method, which solely depends on the inherent

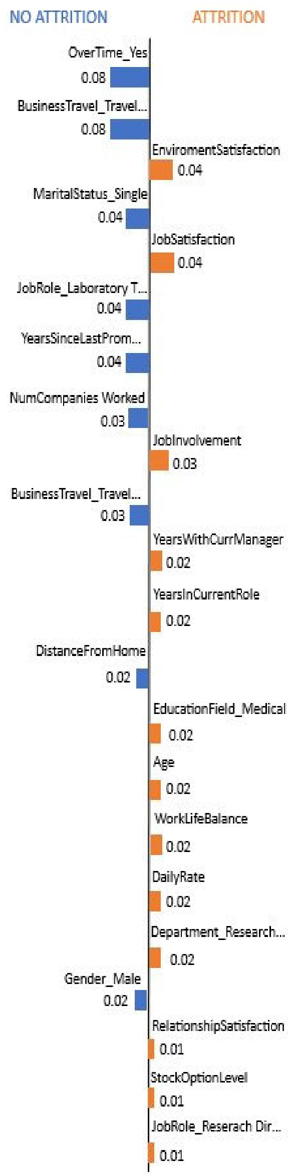

FIGURE 2. XAI results using LIME.

features of the dataset. As highlighted in Table 2, these results stem from a series of experiments conducted using five different ML algorithms. These experiments were conducted under two distinct conditions: one exclusively utilizing the original dataset features, and the other incorporating additional node-embedding 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%. However, the inclusion of node-embedding features resulted in a remarkable improvement of 5% in terms of accuracy across these metrics. Notably, the LGBM exhibited improvement, with an approximately 5% increase in recall, accuracy, F1-measure, and precision. In addition, both the RF and XGBoost models displayed an approximate 4% improvement, whereas the LR model demonstrated the least improvement compared to the others, with only a 3% enhancement. The results clearly indicate that all five ML algorithms performed better when using our proposed method. This highlights the effectiveness of our approach in boosting classification accuracy and shows the potential of using graph-based data representations in ML applications.

It is essential for organizations to identify the factors that predict employee turnover. This is critical to reducing attrition rates, improving employee retention strategies, and creating a more stable and productive workforce. Previous studies have employed various methods to identify these factors. In this study, XAI, particularly LIME, was utilized to determine the factors or traits with the most significant influence on employee turnover prediction. Their findings revealed that environmental satisfaction, job satisfaction, and job involvement were the primary predictors of employee turnover.

The results showed that job satisfaction was the second-most important attribute associated with employee turnover. This encompasses employees' satisfaction and happiness with their roles, considering factors such as workload, relationships with coworkers, and opportunities for career advancement. This confirms the previous findings in the literature, where the authors in [6], [12], [13], and [22] demonstrate that environmental satisfaction impacts employee attrition. Furthermore, this study shows that job involvement is the third factor influencing employee turnover. It denotes employee engagement and commitment to their job tasks and responsibilities, reflecting their dedication and enthusiasm for work. The advantages of employee engagement are noteworthy, especially as they serve as a key factor in minimizing turnover. Disengaged employees often harbor feelings of being ill-prepared, undervalued, and outdated, which influences their propensity to leave [56]. This result is consistent with other results in the literatures [19] and [57], in which the authors stated that job involvement significantly impacts employee turnover. The remaining features related to employee attrition are shown in Fig. 2.

Despite the extensive research conducted on classifying employee turnover, the effectiveness of these studies has room for improvement. One major limitation is that the studies utilized algorithms that do not consider the connections or links between different entities and instead make the assumption that employees within the dataset are not related to or dependent on one another. Recently, KG has been shown to improve the performance of classification models [58]. However, it has not yet been applied to the context of employee turnover.

KG-based solutions have exhibited remarkable results in diverse fields, such as healthcare [52] and education [51]. In this study, we have implemented KG approach on HR datasets containing employee information to uncover latent connections among employees.

TABLE 2. Classification performance when employing original factors and combining original factors with node-embedding features.

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

The proposed method was tested using five ML classification techniques and yielded significantly improved outcomes. We conducted a performance comparison of the models before and after applying KG, which significantly enhanced the accuracy of the model. Specifically, the L-SVM model exhibited an increase in accuracy of 5%. In addition, the accuracy of the RF and GB models increased by 4%, while the LR model improved by 3%.

Furthermore, we compared our methods with those mentioned in the literature, as listed in Table 3. Our method demonstrated superior performance compared to state-of-the-art approaches. The RF model had an accuracy of 89%, which has some similarities with [59], who achieved an accuracy of 85%. While the authors in [58] employed the DTJ48 and NB models, achieving accuracies of 83% and 81%, respectively. The authors in [9] investigated the factors that contribute to employee attrition in a company using various ML methods such as NB, LR, KNN, DT, RF, and SVM to identify the best classifier for the problem. Although they used ML in common with our study and the same dataset, the authors found that the Gaussian Naïve Bayes classifier achieved the best performance. 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, [59] 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.

Using the original dataset, the Quadratic SVM and SVM showed the highest performances at 0.87. Moreover, [60]

TABLE 3. Comparison with state-of-the-art ML models on the original dataset.

Authors	Techniques	Accuracy	Precision	Recall	F1-measure
[9]	Gaussian NB	0.82	0.39	0.54	0.45
	Bernoulli NB	0.84	0.45	0.33	0.38
	LR	0.87	0.66	0.34	0.44
	KNN	0.85	0.55	0.09	0.15
	DT	0.83	0.36	0.36	0.35
	RF	0.86	0.66	0.13	0.19
	SVM	0.86	0.81	0.09	0.17
	L-SVM	0.88	0.66	0.25	0.36
[59]	L- SVM	0.87	0.81	0.24	0.37
	Quadratic SVM	0.87	0.66	0.40	0.50
	Cubic SVM	0.84	0.51	0.42	0.46
	Gaussian SVM	0.86	0.79	0.22	0.34
	RF	0.85	0.75	0.16	0.27
	KNN (K=1)	0.83	0.27	0.05	0.08
	KNN (K=3)	0.84	0.25	0.004	0.008
[60]	DTJ48	0.83	-	-	-
	NB	0.81	-	-	-
[8]	feature selection	0.81	0.43	0.82	0.56
	Without feature selection	0.78	0.39	0.82	0.53
[61]	RF	0.85	-	-	-
[19]	XGBoost	0.89	-	-	-
The Proposed model	**L-SVM (combination with features node)**	**0.925**	**0.92**	**0.93**	**0.92**

used the IBM dataset to evaluate various ML techniques for prediction, such as DT, NB, and k-means. The accuracy of these methods was assessed by implementing a 10-fold cross-validation and a 70:30 train–test split. However, their results may have been better than those of the other studies. This is likely due to the fact that they needed to utilize a data preprocessing step in their work. In their study, [8] proposed a three-stage framework to predict attrition. The first stage involves data reduction using "max-out" feature selection. In the second stage, they trained a predictive LR model. In the third stage, a confidence analysis was conducted to validate the prediction model. Despite these efforts, the accuracy of the system was poor, and the preprocessing and postprocessing stages were extremely complex. The authors in [61] predicted attrition using classification trees and RF. Before data classification, undesirable features were eliminated using Pearson's correlation. The accuracy of their work was better than that of other ML algorithms. Nonetheless, their proposed model indicated higher accuracy than other ML algorithms. However, there may still be room for improvement compared to the findings of alternative research studies. 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. However, these methods currently face challenges in identifying extra-valuable characteristics that can grasp complex data patterns and illustrate employee connections. The proposed approach, which involves converting tabular data into graphs and extracting hidden features, significantly enhances ML classification. When we added node-embedding features to the existing attributes, we obtained better results than the current top-performing ML classification methods that rely solely on the original dataset features. Consequently, our L-SVM model achieved outstanding performance, reaching an accuracy of 92.5%.

V. CONCLUSION AND FUTURE WORK

Employee turnover can profoundly impact an organization, resulting in increased expenses for recruiting and training new staff, decreased productivity, and a decline in employee morale and motivation. Furthermore, it can contribute to reduced customer satisfaction and the depletion of crucial knowledge, skills, and institutional memory, ultimately undermining the overall performance of an organization. Consequently, businesses strive to identify the factors that contribute to employee departure and develop strategies to mitigate attrition. This study introduces a novel approach to predicting employee turnover by leveraging both the original dataset features and features extracted from a graph. Multiple ML models were employed to assess classification performance using different metrics, indicating that L-SVM was the most efficient model. In addition, the L-SVM outperformed the models devised by previous researchers. Moreover, the XAI demonstrates that job environment, job satisfaction, and job involvement are critical factors in employee turnover. In today's competitive business environment, predicting employee turnover has become essential for all types of businesses and institutions, particularly business analysts, managers, and HR executives. Being able to forecast employee turnover enables organizations to take the necessary measures to retain their best-performing staff and avoid the expenses associated with high turnover rates.

An effective approach is to develop a model that can predict employee turnover. This study offers crucial insights into predicting when workers will leave, particularly through the development of a model. Building a predictive model can help organizations recognize the factors that contribute to employee turnover, including low morale, job dissatisfaction, and inadequate opportunities for growth and development. Identifying these factors encourages organizations to take proactive measures to address them, reduce turnover rates, and improve employee retention. Overall, the ability to predict employee turnover using a well-designed model is an effective strategy for organizations to retain the most valuable employees and maintain a competitive edge in their respective industries. Nevertheless, this study makes a significant contribution to both the subject and the researchers. Academics can understand how the method was deployed and learn about the gaps in knowledge and areas that require further analysis. Researchers can use various techniques to transform tableau data into KG to improve the performance of the model. In the future, researchers studying employee turnover could pay more attention to text mining, which involves examining what employees write or say. Using tools such as sentiment analysis and natural language processing, employees can understand how they feel and what they are talking about. This can help predict who might leave the job and why. Researchers may also study how these feelings change over time and ensure they are doing so in a way that respects privacy and ethics. By focusing on text mining, researchers can help companies keep their employees happy and engaged.

In the future, the prediction of employee turnover could greatly benefit from a deeper exploration of psychological and subjective factors. Researchers should consider examining employees' emotions, motivations, and perceptions, which are often key drivers in their decision to stay or leave a job. This might involve using advanced psychological assessments, surveys, and interviews to gain insights into employee well-being, job satisfaction, and a sense of belonging within the organization. By incorporating these nuanced and subjective factors into predictive models, researchers can create a more holistic and accurate picture of turnover risk, as such factors can have wide-ranging implications for an economy that is greatly affected by high employee turnover and low retention [62].

Understanding how these psychological aspects change over time and how they interact with external factors can provide valuable insights into designing effective retention strategies. This multifaceted approach can pave the way for more empathetic and targeted interventions to retain valuable talent within organizations.

In addition, to further our research, we plan to explore alternative methods beyond GCN for converting knowledge graphs into schemas.

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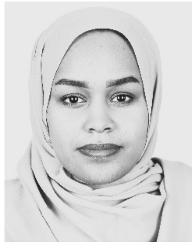

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