Available online at: http://e-jurnal.lppmunsera.org/index.php/INTECH

Jurnal INTECH Teknik Industri Universitas Serang Raya

ISSN (Print) 2407-781X ISSN (Online) 2655-2655

Deep Learning Based Recommendation System for Employee Retention Using Bipartite Link Prediction

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ARTICLE INFORMATION

Article history:

Received: January 9, 2025
Revised: March 4, 2025
Accepted: March 13, 2025

Keywords

Bipartite
Deep Learning
Employee Retention
Link Prediction
Recommendation System

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ABSTRACT

The Human Resources (HR) department faces significant challenges in employee retention. Traditional methods, such as performance evaluations and career development using regression, association, and clustering, have been widely used and have yielded positive results. However, these approaches are limited in predicting changes in employee behaviour and capturing complex relationships between variables. In this study, we leverage AI advancements to enhance predictive analysis by utilizing deep learning's ability to identify patterns and complex relationships while continuously adapting to employee behavior changes. Specifically, we integrate Graph Convolutional Network (GCN) deep learning-based and bipartite graph-based approaches to construct a robust link prediction model. The bipartite employee-training network serves as input to the GCN, where each convolutional layer aggregates information from neighboring nodes, leveraging observed link information at each hidden layer. During the evaluation phase, the model iteratively aggregates information until an optimal state is reached, uncovering hidden relationship patterns that facilitate employee skill development. Empirical results on a benchmark dataset demonstrate significant performance improvements, with precision, recall, and AUC metrics exceeding 80%, highlighting the model's effectiveness in enhancing employee retention.

1. INTRODUCTION

Human resources (HR) plays a pivotal role in business success by managing employees, an organization's most valuable asset. HR is responsible for attracting and retaining top talent while ensuring employees develop skills that drive innovation and productivity. Effective training and development programs enhance employee capabilities and improve job satisfaction, loyalty, and organizational adaptability (Dziuba *et al*., 2020).

Employee satisfaction shapes salary, work environment, interpersonal relationships, and growth opportunities. Confidence in one's skills also plays a crucial role, as employees who feel competent and valued are generally more motivated and productive (Abd-El-Salam, 2023). Similarly, employee loyalty is influenced by job satisfaction and a sense of appreciation, reducing turnover even when external opportunities arise (Ismartaya *et al*., 2023). Research highlights key factors affecting performance, including skills, motivation, leadership, and organizational culture. Companies, therefore, implement training programs to align employee competencies with technological advancements and market demands (Dachner *et al*., 2021; Nath, 2022).

Traditionally, HR training and development rely on manual evaluations, direct observation, and subjective feedback. While useful, these methods are time-consuming, prone to bias, and lack adaptability in responding to organizational changes. As businesses grow in complexity, HR must integrate modern technologies such as artificial intelligence and data analytics to make informed, strategic decisions in talent management.

AI-driven HR solutions offer a more objective, efficient, and precise approach by leveraging big data and predictive analytics. While these models enable deep personalization, they require extensive data and sophisticated infrastructure. Additionally, they often struggle to capture complex employee relationships and remain underutilized in training and development.

This study introduces a deep learning approach using artificial neural networks to address these challenges to improve employee training recommendations and retention strategies. By analyzing complex interactions between performance, satisfaction, and turnover risk, this model generates more accurate predictions and adapts to evolving workforce dynamics.

In summary, the contributions of this paper are outlined as follows:

1. Proposing a deep learning-based recommendation system using a bipartite link prediction model to predict employees who need career development by participating in appropriate training programs.
2. Conducting experiments based on a real-world, large-scale employee dataset to evaluate performance.
3. Analyzing recommendation results and identifying potential performance improvements in the data and algorithms.

This paper is structured as follows: Section 2 provides an overview of related studies on bipartite link prediction. Section 3 discusses bipartite link prediction in employee training for recommendations. Section 4 explains the experiments in detail and presents the results. Section 5 concludes the study, highlighting its limitations and suggesting directions for future work.

2. RESEARCH METHODS

This chapter explores the evolution of Human Resources (HR) systems, focusing on the emerging application of link prediction techniques in bipartite networks to address challenges and enhance performance in organizational settings.

2.1. HR Evolution

Human Resources (HR) has evolved from intuition-based decision-making to data-driven strategies powered by artificial intelligence (AI). Traditionally, HR relied on managerial instincts, with minimal data usage and subjective evaluations based on frameworks like Maslow's hierarchy of needs and Herzberg's two-factor theory (Wan *et al*., 2016). Early improvements incorporated structured motivation models (Porter & Lawler, 1968), but data collection remained limited.

The emergence of descriptive analytics marked a shift toward data-driven HR, tracking turnover rates, demographics, and employee satisfaction (Bilderback & Miller, 2023). Organizations leveraged statistical methods to identify patterns, predict turnover, and improve workforce planning (Davenport & Prusak, 1998; Angrave *et al*., 2016). HR analytics evolved further with big data, enabling evidence-based decision-making (Opatha & Uresha, 2020).

Today, AI-driven HR analytics applies machine learning to large datasets, enhancing workforce predictions, employee engagement, and retention strategies (Murugesan *et al*., 2023; Berhil *et al*., 2019). AI optimizes recruitment, predicts staffing needs, and reduces bias in hiring (Ullman, 2024). However, ethical concerns, privacy issues, and algorithmic bias remain challenges. Approaches like differential privacy and anonymization techniques (e.g., k-anonymity, i-diversity) help protect sensitive employee data.

AI has significantly improved HR processes, from reducing recruitment time (Chaudhuri & Raghunathan, 2021) to optimizing retention strategies using machine learning (Rahman *et al*., 2025). Despite these advancements, AI's application in employee retention remains underutilized, requiring further refinement to balance automation with personalization and ethical considerations.

2.2. Link Prediction

Link prediction aims to forecast potential new connections or identify and remove existing false connections based on the current network structure. This prediction has been successfully applied in various domains, such as predicting gene interactions in biology (X. Ma, 2022), criminal intelligence in social networks (Y. Yao *et al*., 2023), co-authorship analysis in academic collaboration, and sales enhancement in e-commerce by recommending product choices to customers (P. Liu *at al*., 2024). However, the implementation of link prediction for HR is still underexplored. Siregar *et al*. (2024) used Jaccard similarity to assist employee candidates in linking candidates to their competencies. However, this study did not use link prediction, although Jaccard is one of the methods employed in link prediction approaches. One popular link prediction graph model is the bipartite network model, which connects two different entities, such as in academia to link authors and papers (F. Wang *et al*., 2023), in HR job-candidate networks (Eddy *et al*., 2024) and in e-commerce to link customers and products (W. Liu *et al*., 2022).

2.3. Notation and Problem

A bipartite network consists of two types of nodes, where there are no edges connecting nodes within the same set. Edges only connect nodes from one set to nodes in the other set of different groups. Given two sets of objects X and Y, where $X = \{x_1, x_2, \ldots, x_m\}$ and $Y = \{y_1, y_2, \ldots, y_m\}$, graph $G = (V, E)$ is called a bipartite network if X and $Y \in V$ are disjoint sets of nodes or points, meaning $X \cap Y = \emptyset$, and $(x, y) \in E(G)$ represents the set of edges or links, where (x, y) is a pair of nodes with $x \neq y$ and x and $y \in V$.

Based on the definition above, a bipartite network has nodes X and Y, where X represents employees and Y represents training. The goal of bipartite link prediction for employee retention in human resources is to identify missing links from set X to Y, which represents training, as shown by the dashed lines in Fig. 1.

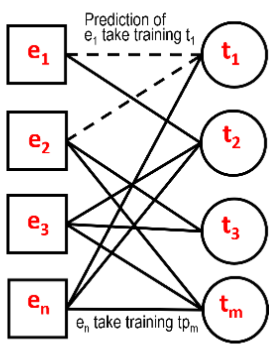

Fig. 1. The structure of bipartite link prediction with nodes *e* (employee) and *t* (training) represents employees and training programs, respectively

http://dx.doi.org/10.30656/intech.v10i1.10069

The working mechanism of bipartite link prediction focuses on modelling the relationships between two distinct sets of entities (*e.g.*, employees and training) in a network, and it is used to predict the likelihood of future connections between these entities. Feature extraction is performed based on the relationships between these two sets of entities. These features may include proximity, frequency of interaction, and the number of direct connections between nodes. For example, two employees who have attended the same training sessions multiple times would be considered more similar.

A deep learning-based machine learning model is used to learn the relationship patterns between entities. This model can capture complex interactions between employees and training. Once the model is trained, predictions are made to determine potential new relationships between employees and training programs that have not yet occurred. For instance, if employee e_1 has not yet attended training t_1, the model will predict whether training t_1 is suitable for employee e_1 based on the patterns found in historical data.

2.4. Deep Learning Model and Bipartite Link Prediction

One of the deep learning models that works on graph-based data is the Graph Convolutional Network (GCN), which enhances traditional neural networks by adding more layers of complexity through connections between nodes. These connections are crucial based on the assumption that identical nodes are more likely to be connected. Nodes have features that represent the attributes or characteristics of each node in the graph. The richer the features of a node, the better GCN can learn meaningful patterns and relationships within the graph. The node features will be extracted and represented by a matrix. GCN is built with layers that repeatedly aggregate information from neighbouring nodes and use it to update the feature representation of each node. Each convolutional layer aggregates and transforms the node's and its neighbours' features.

In Fig. 2, the flowchart starts with the normalization of the dataset, followed by the separation of the dataset into validation, test, and training sets. Each group will be processed differently. The test data serves as input for creating the bipartite structure and training and evaluation in the GCN. The results are used alongside the training data to optimize the model and processed during the training and evaluation phases until optimal conditions are reached, resulting in a deep learning-based prediction model. Meanwhile, the validation data will be used for the prediction process by leveraging the pre-trained deep learning model. The result is a matrix containing link predictions that connect the entities along with their prediction scores.

GCN captures the structural relationships between employee nodes and training program nodes by learning the interactions between the nodes. These interactions are represented by the adjacency matrix, which represents the pairs of nodes (e, t). The adjacency matrix is denoted by A_{ij}, where the element is 1 if node i and node j are connected and 0 if they are not.

Therefore, by adding the adjacency matrix A_{ij} with the identity matrix I, we modify the diagonal elements to I, resulting in A_{ij} as the normalized adjacency matrix. This ensures that each node is connected to itself, and the matrix reflects both the original structure and the self-loops in the graph.

$$\tilde{A} = A + I \tag{1}$$

In an undirected bipartite graph, the GCN structure is represented by the Laplacian matrix L to capture the relationships between nodes. With D as the diagonal matrix, the normalized adjacency matrix $D^{-\frac{1}{2}}$ is calculated as follows:

$$D^{-\frac{1}{2}} = \begin{bmatrix} \frac{1}{\sqrt{d(1)}} & 0 & \cdots & 0 \\ 0 & \frac{1}{\sqrt{d(n)}} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \frac{1}{\sqrt{d(n)}} \end{bmatrix}$$

The GCN operates based on a neural network containing several dense layers. The input for each layer is represented as $\tilde{A}H^{i}W^{i}$, where H^i and W^i are the input features and the learnable weight matrix at layer iii, respectively. The general formula for each layer can be written as:

$$H^{(l+1)} = \tau\,(\tilde{A}H^{(l)}W^{(l)}) \tag{2}$$

Where τ is the propagation function. The output of each hidden layer becomes:

$$H^{(l+1)} = \tau\,(\widetilde{D}^{-1}\tilde{A}H^{(l)}W^{(l)}) \tag{3}$$

As a spectral graph convolution, GCN localizes the first-order approximation with the propagation rule:

$$H^{(l+1)} = \tau\,(\widetilde{D}^{-\frac{1}{2}}\tilde{A}\widetilde{D}^{-\frac{1}{2}}W^{(l)}) \tag{4}$$

To optimize performance, we need to set certain hyperparameters. In the experiment, the number of layers, denoted as k, is set to two, three, or four to prevent over smoothing during information propagation. The hidden layer size, learning rate, momentum term, and dropout rate are also adjusted to prevent overfitting.

Finally, the softmax function is applied to normalize the results, producing the final GCN model:

$$Z = f(x,A) = softmax(\tilde{A}\ ReLU(\tilde{A}XW^{0})W^{1} \tag{5}$$

Where X is the input matrix, W^0 and W^1 are learnable input matrices for transformation to and from the hidden layers, respectively.

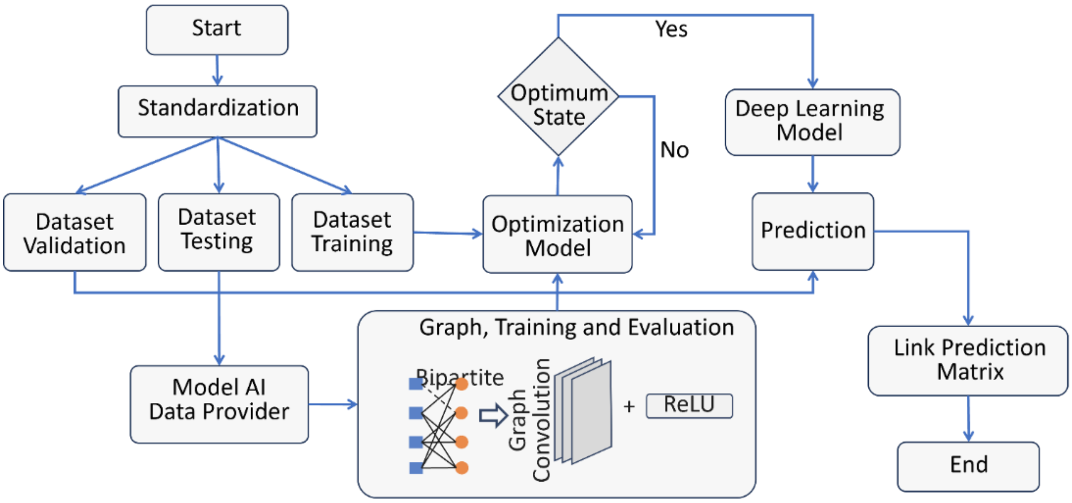

Fig. 2. GCN model of bipartite employee-training link prediction

2.5. Performance of Bipartite Link Prediction

Bipartite represents a graph structure that connects more complex and interrelated entities between two different groups of entities. The relationships represented in this structure will assist in more efficient computation processes as they focus on the connected entities. Without a graph structure, the computation process would be performed for all combination entities, leading to high complexity.

The bipartite structure applied to link prediction will calculate the similarity between entities, capture more complex patterns and relationships, and provide more relevant recommendations in systems that require relationship-based predictions, such as employee development.

Using a regression approach, although effective for linear predictions and single variables, regression is limited to linear or simple relationships between dependent and independent variables and is less effective at capturing more complex relationships or non-linear interactions between variables. Additionally, regression lacks the ability to capture or visualize network structures or relationships between entities in graph form, making it difficult to use for making specific recommendations in situations with many interconnected entities (*e.g.*, training recommendations for newly joined employees) because it does not fully consider the structural relationships between variables.

3. RESULTS AND DISCUSSION

This section presents the experimental design used to evaluate and compare link prediction performance in a bipartite network structure. Based on the available data, the goal is to predict which training program is suitable for a particular employee. This objective is assessed using the GCN model on a real-world market dataset, with evaluation based on accuracy, precision, recall, and AUC metrics.

3.1. Dataset

We evaluate our deep learning-based model using the IBM HR Analytics Employee Attrition & Performance dataset, a publicly accessible benchmark dataset created by IBM data scientists to develop predictive employee retention models. This dataset can be found on the GitHub site under the repository of IBM-HR-Analytics-Employee-Attrition-Performance. Since a bipartite network in this study requires only two disjoint sets, employees and training, we filtered out irrelevant features from the 35 available attributes and retained six key attributes relevant to the link prediction goal: employee, department, job role, job level, work-life balance, and job satisfaction additionally, as the dataset does not explicitly include training program information, a mapping process was employed to derive training-specific attributes, as detailed in Table 1.

Table 1. Conversion of key attributes into appropriate training programs.

No	Attr.	Converted To	Training Program
1	Job Role	Skill-based training	Sales Training Technical Training
2	Department	Department Specific Training	Sales Department Training R&D Department Training
3	Job Level	Training Level	Beginner Training Advanced Training
4	Work-Life Balance	Work-Life Training	Work-Life Training
5	Job Satisfaction	Job Satisfaction Coaching	Job Satisfaction Coaching

To build the appropriate bipartite network, the training needs of each employee are determined based on the following criteria:

a) If an employee is from the sales department and holds the position of sales executive, connect the employee to the sales training node. Do this for all employees in other departments and positions.

http://dx.doi.org/10.30656/intech.v10i1.10069

b) If an employee's job satisfaction is low, connect them to the job satisfaction coaching node. Do this for all employees.
c) If an employee's work-life balance is low, connect them to the work-life balance coaching node. Do this for all employees.

These rules are used to create a relationship table between employees and training categories. From these attributes, employees will be placed on the left node and training on the right node, with attributes attached to the employee nodes as shown in Fig. 3.

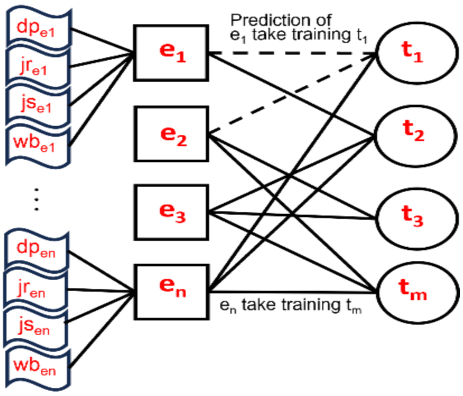

Fig. 3. The graph structure formed is based on the attribute conversion rules into a training program, with attributes attached to employee (*e*) nodes that are connected to the training programs (*t*)

3.2. Metrics

The performance of the recommendations is evaluated based on precision, recall, and AUC as follows:

1) Precision is defined as the proportion of relevant items correctly predicted from the total items predicted. Let N and L represent the total number of recommended training programs and the relevant training programs recommended, respectively. It can be formulated as:

$$Precision = \frac{\mathrm{N}}{\mathrm{L}} \tag{6}$$

2) Recall is the ability to identify missing links. With *m* and *M* representing the existing links and all links, respectively, it can be formulated as

$$Recall = \frac{\mathrm{m}}{\mathrm{M}} \tag{7}$$

3) Area Under Curve (AUC) is the probability that a missing link has a higher score than a non-existent link. For *n* independent comparisons, a missing link and a non-existent link are randomly selected to compare their scores. If n_1 times the missing link has a higher score and n_2 times both have the same score, then AUC is formulated as:

$$AUC = \frac{n_1 + 0.5 * n_2}{n} \tag{8}$$

To reduce incorrect predictions, address the data imbalance (more non-connected than connected), and manage the precision-recall trade-off, a threshold of 0.6 is set, requiring the model to have at least 60% confidence in predicting a positive connection. Higher scores in measurement metrics indicate better accuracy, but AUC remains the primary metric for the model's overall performance.

3.3. Experiment and Analysis

The experiment was conducted on Google Colab using a CPU accelerator with 12 GB of RAM and 120 GB of storage. The Python programming language was used along with several libraries such as NetworkX, PyTorch, and sklearn.

To implement the first rule, a mapping dictionary is implemented that converts department and job role into training programs.

```
# Mapping dictionary for training categories
# The keys are tuples combining Department
# and JobRole (or other attributes as needed)
training_map = {
    ('Sales', 'Sales Executive'): 'Advanced
Sales Training',
    ('Sales', 'Account Manager'): 'Client
Relationship Training',
    ('Research & Development', 'Laboratory
Technician'): 'Lab Safety Training',
    ('Research & Development', 'Research
Scientist'): 'Innovation Training',
    ('Human Resources', 'HR Specialist'):
'Leadership Development',
    # Add more department-role if exist
}
```

To implement the second and third rules, a subroutine is implemented that converts job satisfaction and work-life balance into different training programs.

```
# Function to determine training needs
def categorize_training(row):
    # Lookup training category using Dept
    # and JobRole
    training_category = training_map.get(
        (row['Department'],
         row['JobRole']),
         default_training
    )

    # Add additional conditions
    if row['JobSatisfaction'] < 2:
        return 'Job Satisfaction Coaching'
    if row['WorkLifeBalance'] < 2:
        return 'Work-Life Balance Workshop'

    return training_category
```

Model Training Phase. The bipartite structure is formed with node *e* representing employees on the left side and node *t* representing training programs on the right side, with the connections representing attending training (takes training) as shown in Fig. 4.

In the experiment, dataset sizes with 5 variations were used, ranging from 0.5 to 0.9 for the training data, with the remainder used for evaluation data. For example, if the training data is 0.6, then the evaluation data is 0.4. Hyperparameters used include learning rate α = 0.01, momentum rate β = 0.03, and an architecture with 3 layers of dimensions [32, 32, 32]. The number of

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epochs was set to 100 iterations with early stopping applied to speed up the training process.

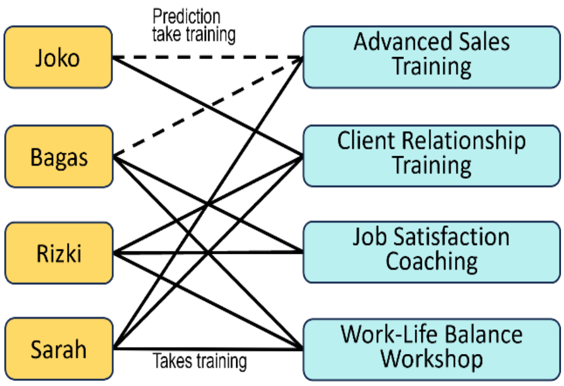

Fig. 4. The graph structure formed follows the bipartite standard, connecting employees with training (solid lines) and predicting whether they are connected or not (dashed lines)

Model Evaluation Phase. The interim model produced during each iteration is evaluated by applying it to the Evaluation data. Each model is measured using metrics such as area under the curve (AUC), precision, and recall. The training and evaluation phases are carried out on data divided into 5 variations, with each variation undergoing 100 iterations. The results of one iteration are measured using the metrics and compared with the results of other iterations. For the 100 iterations, the best model is selected. Since there are 5 variations in total, this process is repeated for the second to the fifth variations. Fig. 5 shows the performance of the model produced for each data size variation, with the best performance observed when the training data size is 0.8.

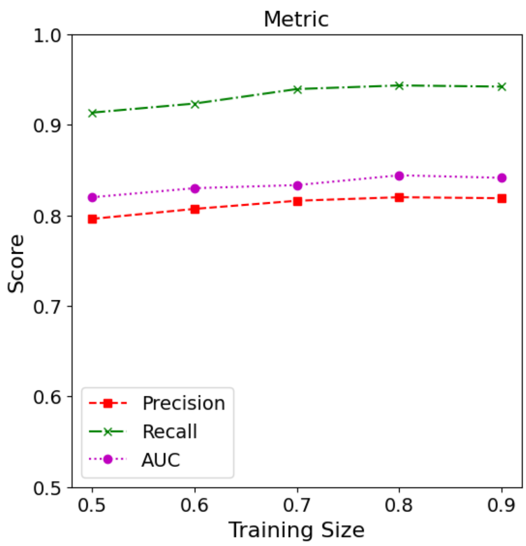

Fig. 5. Performance graph measured based on precision, recall, and AUC against various training data sizes

Using 1,500 employees, the model generated 120 link predictions. After applying a 0.6 accuracy threshold, 90 relationships (80%) met the criteria, ensuring only predictions with the desired accuracy were selected. Fig. 6 shows the bipartite structure of masked employees and training and the link predictions and their corresponding scores for each relationship.

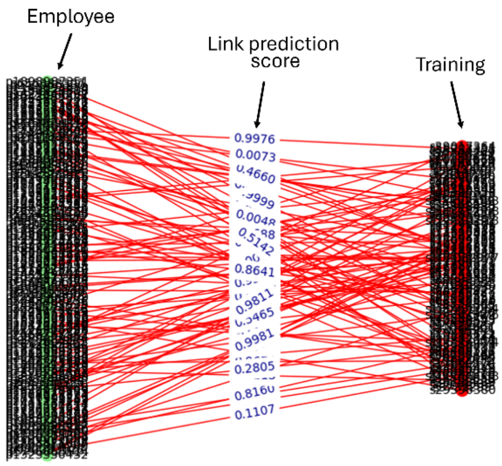

Fig. 6. Bipartite network of employee-training with predicted link scores, indicating potential training assignments based on predicted relevance and employee needs

All the experimental results are summarized in Table 2. An AUC value of 0.8441, accuracy of 0.8585, precision of 0.8199, and recall of 0.9433 indicate a measurement level of around 85% for all the metrics used. Strengthened by the results of filtering that meet the 0.6 threshold, yielding 80%, this demonstrates that the model successfully provides fairly accurate training program recommendations for employees.

Table 2. Evaluation metrics for the bipartite employee-training program with a training data size of 0.8

Metric	**Bipartite (c, p)**	
	Score	#Link > 60%
AUC	**0.8441**	96 of 120 (80%)
Precision	0.8585	
Recall	0.9433	

By applying a link prediction-based approach, strategies can be developed to provide appropriate training for employees based on profile similarities between them. The employee data processed during training is from highly retained employees, which allows the model to perform well. This approach is applied by prioritizing relationships with higher scores, as they are more likely to have a stronger connection.

3.4. Managerial Implication

Bipartite link prediction has several strategic implications that can help management improve employee retention. Here are some managerial

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implications:

a) Personalization and efficiency of employee development programs, by determining the right training for employees based on their interests and potential and aligning it with organizational goals.
b) More accurate identification of turnover risks by considering employees who may be at risk of leaving the company. If an employee is not connected to relevant training or does not receive the necessary skill development, this could be an indicator that they are dissatisfied with the company or feel neglected.
c) Improving organizational performance through early identification of skill gaps within the organization. This will ensure that employees possess the skills required for their job roles, which in turn enhances overall organizational performance.

The implementation of bipartite link prediction in managing employee retention allows companies to be more proactive in improving employee commitment, engagement, satisfaction, and loyalty. For instance, Deloitte applied an AI-driven turnover prediction model to assess employee performance and pinpoint critical factors influencing job satisfaction against organizational loyalty, including career growth limitations and work-life balance concerns (Basnet, 2024). By leveraging these insights, Deloitte effectively anticipated employee attrition risks and enhanced retention through personalized career development program, flexible work arrangements, and targeted compensation policies.

4. CONCLUSION

The use of artificial intelligence in human resource management is becoming increasingly important in addressing the challenges of modern organizations. One crucial application is improving employee retention, which directly impacts the stability and productivity of the organization. By utilizing Graph Convolutional Networks (GCN), companies can develop more accurate and personalized employee training program recommendations. GCN can analyse complex data, such as relationships between employees and other attributes, to identify the most relevant training needs. This approach supports skill development, contributes to employee satisfaction, enhances retention, and supports data-driven HR management strategies.

While this study successfully achieved its objectives, certain limitations remain. First, converting features to optimize training program recommendations has significantly improved prediction accuracy. However, integrating these features as node attributes within the bipartite network may yield even higher precision. Second, to build trust among employee, the study effectively protected employee information by masking credentials with unique codes. However, AI-based approaches may still pose risks of revealing real employee identities. More advanced privacy protection techniques, such as differential privacy and anonymization strategies, are needed to address ethical concerns.

We aim to expand our research in two key directions for future work. First, we plan to integrate node features with the network by assigning relationship weights between employees and training programs based on attributes such as retention, salary, working hours, and other factors. These weighted connections will better represent training needs and improve recommendation accuracy. Second, we will incorporate social relationships among employees to analyse interaction patterns. We can enhance workforce development strategies by understanding how social connections influence training effectiveness and retention. This approach extends beyond direct employee-training links to capture complex social dynamics, offering deeper insights into optimizing training strategies for productivity and well-being. Ultimately, integrating individual attributes with social network analysis will advance data-driven HR management, contributing to more adaptive and intelligent decision-support systems in the future.

COMPETING INTERESTS

The authors state that no financial or personal relationships could have improperly influenced the publication of this paper.

ACKNOWLEDGEMENT

This work was supported by the Ministry of Higher Education Malaysia under Grant FRGS/1/2023/ICT02/UKM/02/2.

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