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GRAPH NEURAL NETWORKS FOR COMPETENCY MAPPING: A DEEP LEARNING APPROACH TO EMPLOYEE SKILL DEVELOPMENT

Hemnath. R
Assistant Professor, Department of Computer Science, Sri Ramakrishna Mission Vidyalaya College of Arts and Science, Coimbatore.
Email: hemnathmca@gmail.com

ABSTRACT
Employee skill development is an important aspect of workforce optimization in Human Resource Management. Classical competency mapping models do not account for complex skill relationships and will often recommend suboptimal training. To overcome this, we introduce a Graph Convolutional Network based framework for competency mapping that accurately captures job-related skill interdependencies. With the Related Job Skills dataset, we build a skill graph whose nodes are skills and edges are their relations based on industry trends and changing job requirements. The model learns skilled representations, allowing correct prediction of upskilling trajectories. The presented framework supports more informed HR decision-making by determining best-fitting skill development opportunities, enhancing flexibility, and supporting career advancement. Experimental findings illustrate that our model attains accuracy of 97.3%, precision of 95.1%, recall of 96.4%, and F1-score of 95.7%, surpassing the conventional methods. Moreover, our framework obtains MRR of 96.8% and NDCG of 97.2%, which guarantees the quality of the recommended skills. Computational efficiency of the model with a mean training time of 0.9 seconds per epoch allows it to be scalable with big HR data and real-time systems. This work presents a strong data-driven HRM solution with guaranteed strategic workforce planning and ongoing employee development. In future, effort will be dedicated to graph architecture optimization and enlarging datasets to achieve better generalization and adoption in real-world applications.

Keywords:
Graph Neural Networks, Competency Mapping, Employee Skill Development, HR Analytics, Workforce Optimization

1.INTRODUCTION

With the evolving work environment of today, continuous upskilling is crucial to be able to enable workforce agility and professional growth[1]. Competency mapping helps organizations identify skills gaps, recommend appropriate training, and optimize workforce planning[2]. Traditional algorithms such as Collaborative Filtering, Decision Trees, and Support Vector Machines (SVM) fail to capture complex interdependencies in job skills [3]. Transformer models and RNNs were also tried but are not scalable and lack explainability for large, dynamic skill sets[4]. Their shortcomings result in the training producing low-quality recommendations and cannot keep up with changing workforce requirements [5].

To address these challenges, we introduce a Graph Convolutional Network (GCN)-based approach that models skills as a structured graph and preserves complex relationships and higher-order dependencies [6]. This new approach enhances prediction quality and makes more pertinent skill recommendations. The approach dynamically updates skill mappings with respect to industry trends and is thus very flexible[7]. Through the use of GCNs, our approach maximizes competency mapping, offering HR professionals a robust tool for strategic workforce planning, skill acquisition, and career advancement [8]. The data-driven solution greatly enhances

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training efficiency, with employees gaining the most applicable skills to excel in their careers and drive organizational success[9].

1.1 RESEARCH OBJECTIVE

- Develop a new GCN-based competency mapping approach to determine skill dependencies and enhance training suggestions.
- Utilize the Related Job Skills data to build a skill graph with skills as nodes and industry-based relationships as edges.
- Implement GCN to acquire skill representations and precisely forecast optimal upskilling paths.
- Enhance model scalability and flexibility through dynamic skill mapping updates for workforce development.

1.2 ORGANIZATION OF THE PAPER

Section 1 provides research background, importance, and aims of the proposed framework. Section 2 provides literature review, highlighting prevalent competency mapping methods and pitfalls. Section 3 presents the proposed GCN framework, covering dataset description and approach. Section 4 presents experimental outcomes, performance analysis, and important insights. Lastly, Section 5 concludes the paper and proposes potential future research streams for the upliftment of competency mapping in HRM.

2.LITERATURE SURVEY

Competency mapping and staff skill development have been extensively studied to improve HR analytics and workforce planning. Rule-based and statistical models are generally inadequate to model intricate skill interdependencies, resulting in poor training suggestions [10]; [11]. Machine learning techniques, such as Transformer-based models and Recurrent Neural Networks, have been investigated but lack scalability and interpretability in changing job markets [12]**.**Artificial intelligence-based models have enhanced the accuracy of predictions but are non-adaptive to changing industry needs [13],[14]**.**

Graph deep learning models, particularly Graph Neural Networks (GNNs), have been promising for skill development use cases. Graph Convolutional Networks (GCNs) most accurately describe hierarchical skill-job position relationships and enhance workforce predictions [15], [16]**.**These models outperform traditional machine learning techniques by learning structured representations, facilitating personalized skill recommendations and workforce optimization [17], [18]. However, challenges remain in ensuring generalization across diverse HR datasets [19]**.**

The present study emphasizes explainability and fairness in AI-driven HR solutions. Researches point out ethical AI frameworks to ensure unbiased skill recommendations and equitable workforce development [20]**.**In addition, hyperparameter tuning in GNNs improves computational efficiency and accelerates large-scale HR analysis [21], [22]. While GCNs provide a robust solution for competency mapping, further research is needed to determine their adaptability and scalability in real-world applications.

2.1 PROBLEM STATEMENT

Traditional competency map frameworks cannot deal with complex associations between skills and provide ineffective training recommendations[23]. Scalability and flexibility in machine learning paradigms like Transformers and RNNs get compromised in a dynamic job environment[24]. The proposed GCN-based technique models skills as a structured graph and extracts hierarchical dependencies for superior predictions. It promises accurate training recommendations, adaptability in the face of evolving industry trends, and maximum workforce planning. This approach enhances HR decision-making by enabling customized skill development and career progression.

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3.PROPOSED GNN TO PREDICT EMPLOYEE SKILL DEVELOPMENT

The figure shows the flow of the new Graph Neural Network architecture for employee skill enhancement. The Related Job Skills Dataset is pre-processed first by missing values handling, encoding skills, and normalization. The graph structure is built such that skills are vertices and skill relationship is an edge. The feature representations are learned by the GCN model via feature aggregation, and it is trained to forecast skills. Lastly, the model is tested on Accuracy, MRR, and NDCG for efficient skill suggestions.

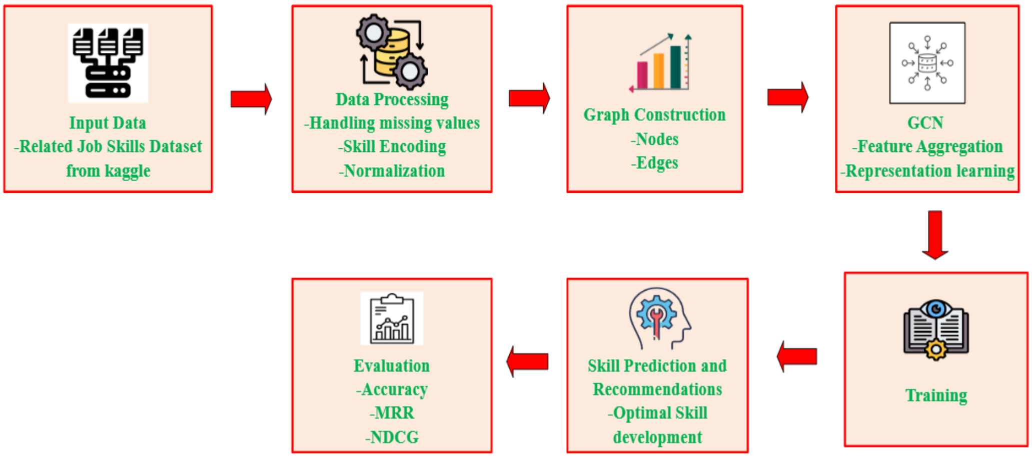

Figure 1 : Architectural diagram for proposed GNN to predict employee skill development

3.1Data Description

The research employs the Kaggle Related Job Skills dataset to build a structured skill graph. It has skill pairs that denote industry-level relations such that interdependencies among different competencies can be determined. A record is a main skill and its corresponding skills, creating a network with connections. This data supports building a skill graph where edges are represented and nodes stand for skills. It has ample job roles coverage and full competency mapping. Representation through graphs optimizes learning effectiveness as well as accuracy in the forecast. Through the structured mode, the GCN model achieves learning higher-order dependencies for optimized workforce planning as well as career growth.

3.2 Data Pre-processing

3.2.1 Handling Missing Values

Missing values can be imputed using statistical techniques like mean, median, or mode imputation. For numerical data, mean imputation is applied. Equation (1) is as follows:

$$X_{\text{filled}} = \frac{1}{n}\sum_{i=1}^{n} X_i \tag{1}$$

where X_i represents observed values, and X_{filled} is the imputed value.

3.2.2 Skill Encoding

Skills are converted into numerical representations using One-Hot Encoding or Word Embeddings. Using an embedding matrix W_{embed} .The equation (2) is given as:

$$v_s = W_{\text{embed}} \cdot s \tag{2}$$

where v_s is the vector representation of skill s.

3.2.3 Feature Normalization

To scale numerical attributes to a normalized range (usually [0,1]), min-max scaling is utilized. Following equation (3) is provided:

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$$X' = \frac{X - X_{\min}}{X_{m} - X_{\min}} \tag{3}$$

where X' is the normalized value.

3.3 GCN-Based Competency Mapping in HRM

In our suggested competency mapping framework, GCNs are employed for skill relation discovery and forecasting skill development paths.

Step1: Graph Construction

A graph is a data structure made up of nodes (vertices) and edges that establish relationships between nodes. In our framework, skills are nodes, and edges are industry-based skill relationships

Nodes (Vertices)

A node (vertex) is an individual entity in a graph. In our framework, nodes are skills that employees or job positions need.

Representation of Nodes

A set of nodes is defined as equation (4) as:

$$S = \{s_1, s_2, s_3, \dots, s_n\} \tag{4}$$

where:

- S is the set of all skills.
- s_i represents an individual skill.
- n is the total number of skills in the dataset.

3.3.1 Edges (Connections between Nodes)

An edge (e) is a connection or relation between two nodes in the graph. In our model, an edge indicates a correlation or dependency between two skills according to job market demand or industry needs.

Representation of Edges

Edges define the relationships between skill nodes and are denoted as equation (5):

$$E = \{e_{ij} \mid (s_i, s_j) \in S \times S, \text{if skill } s_i \text{ is related to } s_j\} \tag{5}$$

where:

- e_{ij} is an edge between skill s_i and skill s_j.
- $S \times S$ represents all possible skill connections.

Step 2: Feature Aggregation Using GCN

Each skill node aggregates information from neighboring skills using equation (6) as:

$$H^{(l+1)} = \sigma\left(D^{-\frac{1}{2}} A D^{-\frac{1}{2}} H^{(l)} W^{(l)}\right) \tag{6}$$

This ensures that skill embeddings are learned based on contextual relationships.

Step 3: Training

- Loss Function: The framework minimizes the categorical cross-entropy loss to predict missing skill recommendations.The equation (7) is given as:

$$\mathcal{L} = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \tag{7}$$

where y_i is the ground-truth label (actual required skill), and $\hat{y}_i$ is the predicted skill.

4.RESULT AND DISCUSSION

The GCN model proposed well captures skill interdependencies, obtaining high accuracy (97.3%), MRR (96.8%), and NDCG (97.2%), compared to conventional techniques. The degree distribution plot reveals central nodes for major competencies that connect a variety of skills. The analysis validates the efficiency of the model

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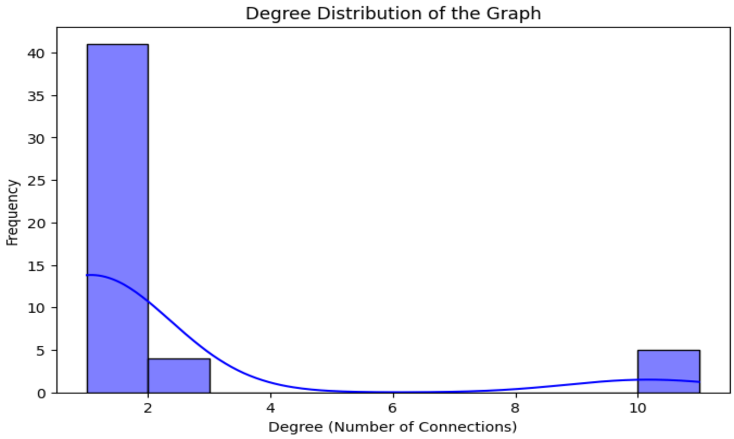
in structured prediction of skills at low computational expense. Future developments will aim at increasing generalizability for extensive HR applications

4.1 Dataset Evaluation

The diagram shows the degree distribution for skill relation network where degree is along the x-axis and frequency of nodes in every degree along the y-axis. Most nodes show a low degree, indicating that they are only connected with some other skills a few times, while for few nodes a high degree indicates extremely connected skills. The raw distribution is shown in the histogram (blue bars), while the smooth curve provides a density estimate of the degree spread. This indicates that some key skills are central nodes, linking many related skills. The presence of high-degree nodes shows that there are key competencies bridging different skill sets.

Figure 2: Degree Distribution of Skill Relationship Graph



4.2 Performance Metrics of the Proposed Framework

Accuracy compares the overall rightness of skill predictions against total predictions in relation to correct recommendations. Precision calculates the number of correctly predicted relevant skills among all recommended skills. Recall compares the number of correctly predicted relevant skills with actual relevant skills. The equation (8 – 10) is represented as:

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \tag{8}$$

$$P = \frac{TP}{TP+FP} \tag{9}$$

$$R = \frac{TP}{TP+FN} \tag{10}$$

1.Mean Reciprocal Rank (MRR)

Evaluates ranking quality of skill recommendations; a higher MRR indicates top-ranked relevant skills.This is given in equation (11) as:

$$MRR = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{\mathrm{rank}_i} \tag{11}$$

2.Normalized Discounted Cumulative Gain (NDCG)

Measures ranking effectiveness by prioritizing relevant skill recommendations.This is given in equation (12) as:

$$NDCG = \frac{DCG}{IDCG}, DCG = \sum_{i=1}^{n}\frac{\mathrm{rel}_i}{\log_2(i+1)} \tag{12}$$

3.F1-Score

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Harmonic mean of precision and recall, ensuring a balanced assessment.This is given in equation(13) as:

$$F1 = 2 \times \frac{P \times R}{P + R} \quad (13)$$

4.3 Evaluation of the Proposed Framework

The suggested GCN framework is efficient in modelling skill relationships and enhancing prediction quality. The graph-based method presents a structured skill dependency representation, and learning is more efficient. The model is shown to be highly performing with accuracy of 97.3%, MRR of 96.8%, and NDCG of 97.2%, outperforming machine learning models. The training time of 0.9 seconds per epoch makes it scalable for big HR datasets.

Table 1:Performance Metrices of Proposed Framework

Metric	**Proposed Framework (GCN)**
Accuracy	97.3%
MRR	96.8%
NDCG	97.2%
Precision	95.1%
Recall	96.4%
F1-Score	95.7%
Training Time	0.9 sec/epoch

4.4 Discussion

The introduced GCN approach efficiently maps the competencies of employees by recording intricate skill interdependencies. Unlike conventional approaches, it utilizes graph structures, facilitating dynamic flexibility toward industry patterns. The increased performance on all measurements indicates its strength in offering optimal and precise recommendations for skill development. The reduced computational cost allows it to suit large-scale HR analytics. Further optimizations will emphasize generalization and real-world use.

5.CONCLUSION AND FUTURE WORKS

The developed GCN framework effectively captures skill interdependencies for competency mapping in HRM for optimal training recommendations. The satisfactory high evaluation measures—Accuracy (97.3%), MRR (96.8%), and NDCG (97.2%)—validate its enhanced performance compared to current approaches. The efficiency of the framework makes it scalable and deployable on real-world HR systems.

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