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# Analyzing Collaborative Learning in Peer Education Using Deep Graph Neural Networks

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## Abstract

Peer education has gained importance in the contemporary education systems because of its capacity to enhance student interaction, engagement and performance at school. Nonetheless, the conventional ways of evaluation do not adequately represent the dynamic and detailed associations among learners. This paper overcomes this limitation and presents a Deep Graph Neural Network (DGNN)-based model to investigate the analysis of collaborative learning in peer education settings. The research technique will be to model the relationships of learning, peer pressure, and group dynamics by using the graph structure to model the students as nodes and their interactions as edges. The data is comprised of 2300 student nodes with interaction weighted edges and a weekly time window that represents temporal learning behaviour. The proposed model combines the graph representation learning, attention systems and temporal feature modelling to enhance predictive performance. As experiment results demonstrate, the baseline model will have an accuracy of 0.74 and F1-score of 0.72, whereas the introduction of Graph Neural Networks will lead to an increase in the accuracy to 0.87 and F1-score to 0.85. Additional improvements with temporal characteristics bring the results to 0.89 accuracy and 0.88 F1-score. Attention-based GAT model has the highest accuracy of 0.91 and F1-score of 0.90, whereas the full DGNN proposed model has the highest accuracy of 0.93 and F1-score of 0.95. The findings show that the combination of graph learning, temporal dynamics and attention mechanisms to collaborative learning analysis shown considerable positive impact. The research reaches the conclusion that DGNN is a powerful and efficient model to study the patterns of peer interaction, to find the influential learners and to predict education performance in the collaborative learning setting.

Keywords

Deep Graph Neural Networks, Collaborative Learning, Peer Education, Graph Representation Learning, Student Performance Prediction, Attention Mechanism, Educational Data Mining.

## 1. Introduction

Peer education is a new phenomenon that has proved to be an effective strategy to improve the engagement of students, sharing of knowledge, and general performance in the contemporary learning settings. It also makes the learners interact, discuss and solve problems together, which results into better comprehension and learning outcomes. Nevertheless, conventional ways of assessing collaboration can seldom embody the dynamic and intricate relationships that occur between students in actual learning contexts. As artificial intelligence progresses, the use of deep learning methods has been proposed to study student behaviour and interaction patterns in a more efficient way. Specifically, graph-based learning models like Deep Graph Neural Networks offer a strong means to represent students as the connected nodes and structure their relationships in a systematic fashion. Compared to traditional methods, these models assist in determining group dynamics and patterns of interaction, influential learners, and help avoid misconceptions [21]. Thus, the given work is devoted to the analysis of collaborative learning within the framework of peer education based on Deep Graph Neural Networks to gain better insight and evaluation of collaboration among students in the educational system. Learning strategies of collaborative learning contribute greatly to the improvement of student academic performance as its promote interaction and understanding. Learning environments become better motivated, more engaged, and more problem-solving with peer-based education [1]. Collaborative learning has been studied using Deep neural networks by examining collaborative learning with Behavioural signals e.g. gaze tracking. These models assist in assessing the quality of interaction of the team but are still not structurally relationship modelling among the students [2]. Stacked Graph Neural Networks (GNNs) are useful in the detection of learning communities in social and educational networks. To enhance the knowledge of group formation and group behaviour patterns in learning peer groups [3]. The student interaction networks in collaborative learning systems are modeled by the use of Graph Convolutional Neural Networks (GCNNs). Which is assist in evaluating teamwork capacity by taking relational dependencies amid learners [4]. Machine learning methods are developed that are hybrid to detect influential nodes in social and collaborative networks. Such techniques can be used to identify significant individuals who can significantly influence group learning effectiveness [5]. Graph analysis-based deep learning enhances recommendations in online learning systems. It improves personalization of learning by modeling relationships between learning resources and students [6]. GNNs are extensively implemented in smart education to model patterns of student interaction. To facilitate performance forecasting, adaptive learning and learning decision-making systems [7][24]. Deep learning networks are useful in forecasting the performance of students in schools. Nevertheless, to find it hard to embrace dynamic and changing collaboration behaviour among learners [8]. The use of Graph Convolutional Networks in classroom grade assessment and educational evaluation. In this enhance accuracy in prediction, although Which are still not able to effectively collaborate in real-time learning [9][10]. Cooperative Machine learning has been shown to have a positive impact on academic development and student success. It enhances the exchange of knowledge and increases the general learning performance in peer-based contexts [20][25].

### Key Contribution

- In this work, a Deep Graph Neural Network (DGNN) architecture is created to model students as nodes and their interactions as edges, which would allow us to analyze the dynamics of collaborative learning in a peer education setup in a structured manner.
- The proposed method is effective to detect the hidden patterns of interaction and recognize influential learners in the peer groups enhancing the knowledge of the collaboration strength and knowledge diffusion.
- The model offers a more precise evaluation of student collaboration incorporating relational learning and thus the better prediction and evaluation of effectiveness of peer education than the traditional ones.

This research covers by the following references, section I explained about introduction about topic, Section II explained the summary of the related work, Section III explained the System Overview consists of System architecture, Deep Graph for Neural Network in peer educations. Section IV explained about dataset description, Hardware and software configurations, Parameter initializations, Model Training results, Hyper parameter tuning results, Prediction results, Performance comparison of Baseline with DGNN and ablation study analysis. Section V explained about conclusion of this research.

## 2. Literature Review

**Table 1: Summary of Related Work**

| Reference | Method / Model | Key Focus | Key Findings / Contribution |
|---|---|---|---|
| [11] | Graph Neural Network (GNN) | Learner performance prediction | GNN improves accuracy in predicting student performance by modelling relational learning structures in educational data. |
| [12] | GOAT (Graph Transformer Framework) | Student performance in collaborative learning | Combines global-local graph transformer optimization to enhance prediction accuracy in collaborative environments. |
| [13] | AI-based learning analytics model | Student learning performance in higher education | Demonstrates AI improves learning outcomes through multinational educational collaboration and adaptive analytics. |
| [14] | Graph Neural Network recommender system | Personalized learning recommendations | GNN-based recommendation systems improve personalization of learning paths based on student interaction data. |
| [15] | FedGraphHE (Federated GNN) | Privacy-preserving collaborative learning | Introduces federated GNN with homomorphic encryption ensuring secure and privacy-preserving learning analytics. |
| [16] | Social Network Analysis (SNA) | Network-based prediction modelling | Uses graph-based analysis to identify interaction hotspots and predict conflict patterns in complex networks. |
| [17] | Multimodal Learning Analytics (MMLA) | Collaborative learning participation dynamics | Analyses participation differences in collaborative learning using multimodal Behavioural data. |
| [18] | AI-driven collaborative learning framework | Peer interaction and knowledge sharing | Enhances collaboration and knowledge sharing efficiency in online learning environments using AI-based modelling. |
| [19] | Bibliometric + Topic Modelling | Learner emotions in collaboration | Identifies emotional patterns affecting collaborative learning effectiveness using large-scale textual analysis. |
| [22] | Influence prediction model | Collaboration network influence analysis | Predicts influence propagation in collaboration networks using graph-based statistical modelling. |
| [23] | Study-GNN (Multi-topology GNN) | Student performance prediction | Improves prediction accuracy by integrating multiple graph structures representing student learning behaviour. |

Table 1 presents the literature review demonstrates the increasing importance of graph-based and AI-based methods of studying collaborative learning and predicting student performance. Research like [11] illustrates that Graph Neural Networks (GNNs) are effective to enhance learner performance prediction by observing the relational dependencies in educational data. In more sophisticated transformer-enhanced architectures such as GOAT in [12][26], the prediction accuracy can be improved by incorporating both global and local graph representations to collaborative learning settings. The AI-based learning analytics models presented in [13] demonstrate that a smart system can considerably enhance the learning process by providing adaptive and data-driven learning assistance. Besides that, the GNN-based recommender systems in [14] enhance personalized learning by better modelling interaction patterns between students. Privacy-preserving mechanisms, like FedGraphHE in [15] take these further by allowing secure collaborative learning with federated graph learning and encryption. In addition to education specific models, social network analysis techniques in [16] also show how graph-based techniques can be useful in determining interaction hotspots and Behavioural patterns in complex systems. The [17] Multimodal Learning Analytics also adds to the comprehension of collaborative participation with the incorporation of Behavioural and contextual data. The [18] AI-based collaborative learning systems improve the process of peer interaction and sharing knowledge in the online learning setting. Bibliometric and topic modelling-based studies of learner emotions in [19] point to the role of emotional factors in the effectiveness of collaboration. The models of influence prediction in [20][27] are useful as to recognize important nodes and propagation patterns on collaboration networks. Lastly, the study-GNN in [23] validates that multi-topology graph neural network is highly effective in predicting performance of students because it considers a wide range of structural relationships in learning behaviour. All in all, these investigations all lead to the conclusion that graph-based deep learning models could serve as an effective foundation to study collaborative learning, but the current problems about dynamic interaction modelling and real-time adaptation still exist.

## 3. System Overview

### 3.1 System Architecture for Analyzing Collaborative Learning in Peer Education Using Deep Graph Neural Networks

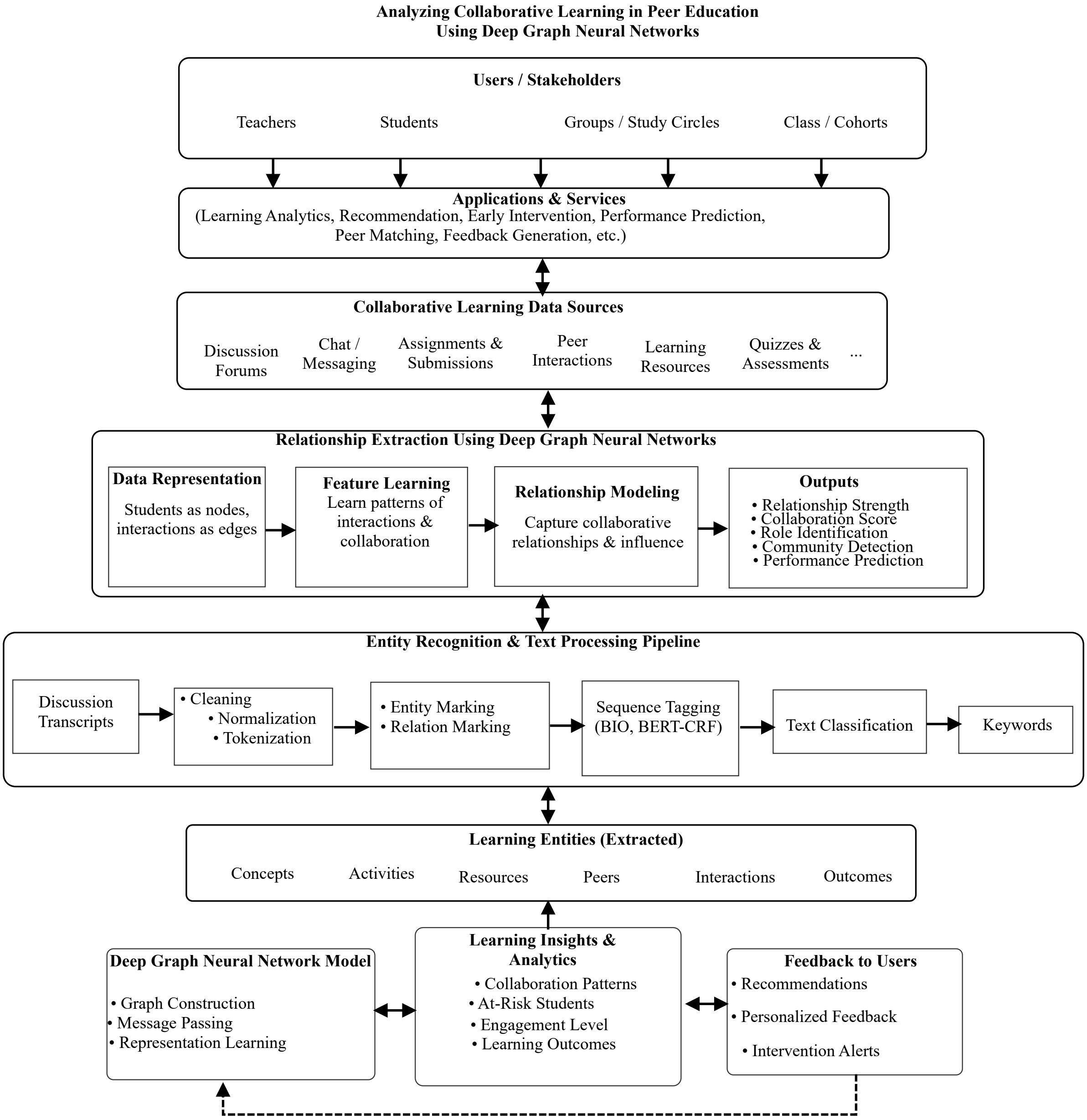

**Figure 1: System Architecture for Analyzing collaborative Learning in Peer Education using Deep Graph Neural Networks**

Fig1 shows the proposed framework that depicts an intelligent collaborative learning analysis system of peer education utilizing Deep Graph Neural Networks (DGNNs). It starts with several stakeholders such as teachers, students, study groups and classroom cohorts who engage in peer learning environment. These interactions are supported through various educational applications and services such as learning analytics, recommendation systems, peer matching, feedback generation, and performance prediction. The data of collaborative learning are gathered through various data sources such as discussion forums, chat systems, assignments, peer interaction, learning materials, and quizzes. This is followed by the application of Deep Graph Neural Network-based relationship extraction that the students and interactions are modeled as graph nodes and graph edges to learn collaborative pattern, influence, and the strength of interaction. The relationship modeling and feature learning are useful in determining collaboration scores, community structures, role identification and prediction of learning performance. In parallel, discussion transcripts are preprocessed by an entity recognition and text processing pipeline that cleans, annotates, sequence tags, text classifies and matches keywords to identify meaningful educational entities, including concepts, activities, resources, peer interactions and learning outcomes. The DGNN model also conducts graph-building, message-passing and representation-learning to produce more in-depth learning insights and analytics, such as engagement rates, identification of students at risk, collaboration behavior, and academic performance. Lastly, the system also offers personalized feedbacks, recommendations and intervention alerts to users to provide adaptive and data-driven peer education support to enhance learner collaboration and performance.

### 3.2 Deep Graph Neural Networks in Peer Education

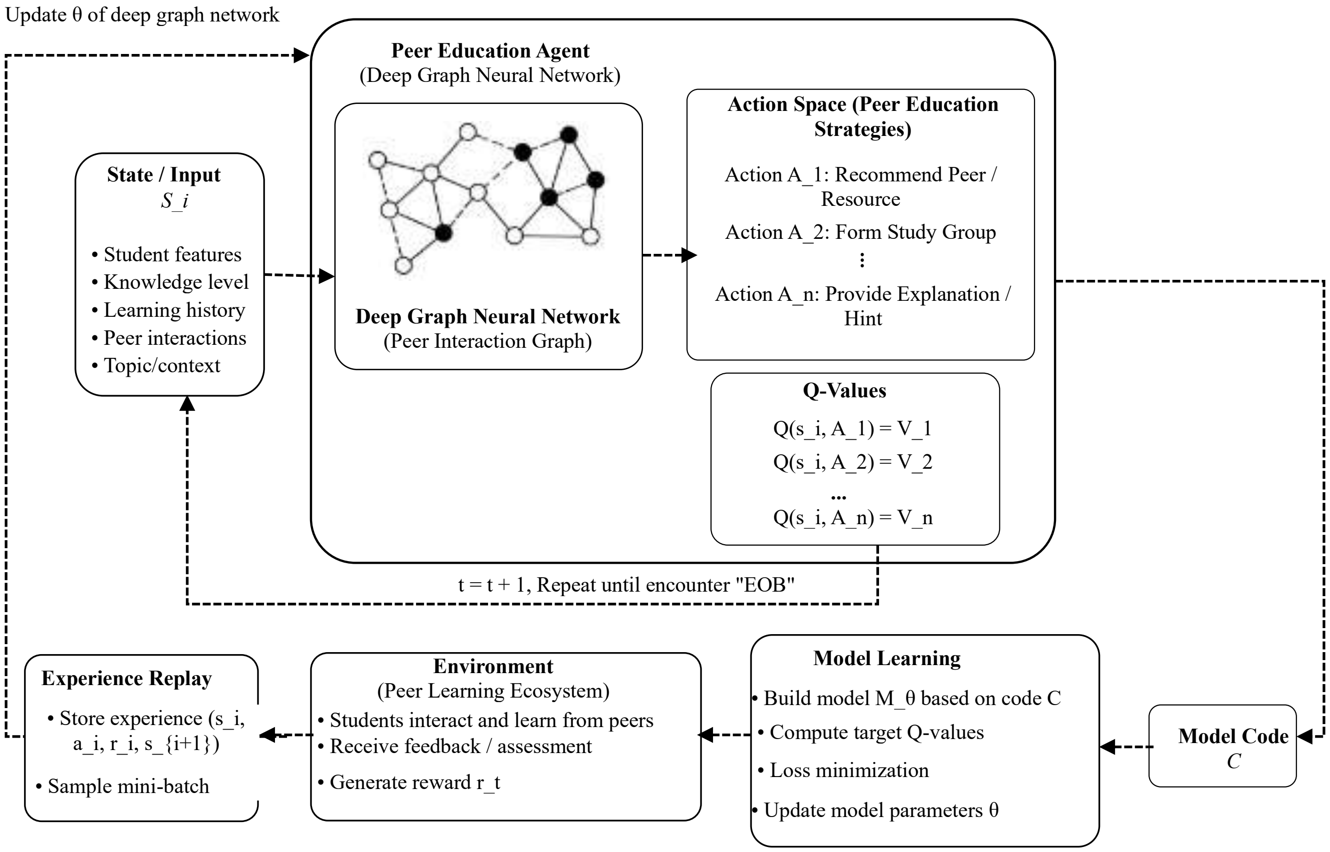

**Figure 2: Working procedure of Deep Graph Neural Networks in Peer Education**

Figure 2 Shows The proposed framework demonstrates a Deep Graph Neural Network (DGNN)-based peer education system that aims to analyze collaborative learning interactions and optimize them in a peer learning ecosystem. The process starts by gathering learner-related inputs, such as the features of students, their level of knowledge, their learning history, interaction with peers, and the context of the topic, which combined comprise the state representation of the learning environment. The Peer Education Agent processes these inputs and a Deep Graph Neural Network models the peer interaction graph to learners, capturing the relationships, communication patterns and knowledge sharing behaviour between learners. Using these graph representations, the system decides the appropriate peer education strategies using an action space that involves the recommendation of peers or learning materials, the formation of study groups and explanations or hints. Q-values are used to assess the effectiveness of the chosen educational strategy to enhance the performance and engagement of learners. The environment module is a reflection of the real peer learning ecosystem where students communicate, get feedback or assessments, and create reward based on the learning results. The learning experiences that are generated are saved in experience replay module where past interaction data can be reused effectively and consistently to train the system. In model learning, the framework calculates the target Q-values, loss reduction, and continuously optimizes the parameters of the DGNN model to enhance prediction and decision-making achievements. This repetitive cycle goes on until the learning session is at the end condition, so that the framework can dynamically optimize peer education strategies, reinforce collaboration learning effectiveness, and provide adaptive-looking educational decision-making by intelligent graph-based analysis.

In the message-passing graph neural networks, the aggregating neighborhood uses aggregation and combination operations to capture the information from neighbor nodes that are one or more hops away from the target node. The operation on node at the $k$ −th graph neural network layer can be defined as follows:

$$h_i^{(l)} = combine^{(l)}\left(h_i^{(l-1)}, a_i^{(l)}\right) \tag{1}$$

From the above Equation (1) describes the

$$a_i^{(l)} = Aggregate^{(l)}\left(\left\{h_j^{(l-1)}; v_j \in N(v_i)\right\}\right) \tag{2}$$

From the above Equation (2) defined as $h_i^{(l)}$ as the feature vector among the node $v_i$ in the lth layer and $h_i^{(0)} = x_i$, $N(V_i)$ Should represents the set of the neighbor node of $v_i$ $combine\ (.)and\ Aggregate(.)$. The result should be specified in the different models for different values of $N(V_i)$. For an instance two-layer GCN equation can be defined as,

$$Z = Softmax\left(AReLU\left(AXW^{(o)}\right)W^{(1)}\right) \tag{3}$$

From the Above Equation (3) describes the $A = D, A, D$ should represents the degree matrix among the adjacency matrix of the self-loops.

## 4. Experiment Results and Analysis

### 4.1 Dataset Description

The simulated dataset in this research is a simulated collaborative learning dataset that is meant to approximate peer education in a structured learning setting. It comprises 2300 student nodes with each node representing a single learner. Interaction frequency and interaction type are used to model the relationships between the students and to create weighted edges in the graph structure. The data set provides a variety of measures of student activity, such as participation in discussions, submitting assignments, communicating with peers, using learning materials, and achieving quiz results. In order to include the time learning dynamics, the dataset is split into a time window of 1 week, 1 = 1 week and the model can learn to capture collaboration patterns as time progresses [20]. This temporal discontinuity assists in examining variations in student behaviour and performance development in various stages of learning. The data set is designed explicitly to facilitate graph-based learning models and thus Deep Graph Neural Networks can be effectively used to analyze collaborative learning.

### 4.2 Hardware Software Configuration

Table 2 presents the hardware and software setup in this study offers a powerful and efficient platform on which deep graph neural network based collaborative learning analysis can be conducted. The system is developed on the Intel Core i7 multi-core processor with 16 GB (or more) RAM, which will process large-scale graph computation and student interaction data efficiently. It uses a dedicated NVIDIA graphics card with at least 8 GB of VRAM and CUDA capability to provide faster training of deep learning models and optimal computational efficiency on graph-based architectures. A high-speed SSD system manages data storage, thus increasing data retrieval and processing speed. Its experimental setup is based on either Ubuntu 20.04 LTS or Windows 11, and Python 3.8+ as the main programming language to implement the models. Deep learning architectures like TensorFlow and PyTorch are used to develop models, and graph-based computations are assisted by PyTorch

Geometric and DGL libraries. Moreover, NumPy, Pandas and Scikit-learn are used to process and analyze data and Matplotlib and Seaborn are used to visualize findings. In general, this combined design guarantees scalable, efficient, and precise analysis of collaborative learning with deep graph neural networks.

***Table 2:* Hardware *and Software Configurations***

| Category | Specification |
|---|---|
| Processor | Intel Core i7 / Multi-core CPU |
| RAM | 16 GB or higher |
| GPU | NVIDIA GPU (minimum 8 GB VRAM, CUDA enabled) |
| Storage | SSD storage system |
| Operating System | Ubuntu 20.04 LTS / Windows 11 |
| Programming Language | Python 3.8+ |
| Deep Learning Framework | TensorFlow / PyTorch |
| Graph Libraries | PyTorch Geometric / DGL |
| Data Processing | NumPy, Pandas, Scikit-learn |
| Visualization Tools | Matplotlib, Seaborn |

### *4.3 Parameter Initialization*

***Table 3: Parameter* Initialization**

| Parameter | Value / Configuration |
|---|---|
| Learning Rate | 0.005 (optimal), 0.001 (baseline test) |
| Batch Size | 128 |
| Epochs | 200 |
| Optimizer | Adam |
| Loss Function | Cross-Entropy Loss |
| Attention Heads | 4, 8 (tested configurations) |
| Dropout Rate | 0.2 |
| Time Window (Δt) | 1 Week |
| Number of Nodes | 2,300 |
| Edge Weight Basis | Interaction frequency + type |
| Activation Function | ReLU / GELU |
| Best Configuration | LR = 0.005, Attention Heads = 8 |

Table 3 demonstrates that the parameterization of the proposed model is set to guarantee the stable training and the best performance of the collaborative learning analysis with the Deep Graph Neural Networks. The learning rate, which is 0.005, is considered the best, and a learning rate of 0.001 is applied as a benchmark, a batch size of 128, and training is performed over 200 epochs. Adam optimizer is combined with cross-entropy loss function to maximize efficiency in converting to the truth. This model uses 4 and 8 attention heads that can be experimented with, and the dropout rate is set to 0.2 to prevent overfitting. Data is organized with a time window 1 week, with 2,300 nodes, and where the value of the edge is the frequency and nature of interactions of the two nodes. The use of activation functions, like ReLU and GELU, enhances non-linear feature learning. In general, the optimal model is obtained at a learning rate of 0.005 and 8 attention heads that offers high accuracy and stability in predicting collaborative learning patterns.

### *4.4. Metric Evaluation*

The proposed Deep Graph Neural Network (DGNN) model is tested based on Accuracy, Precision, Recall, F1-Score and Top-10 Accuracy. Accuracy is used to measure the overall accuracy of the model in predicting the results of collaborative learning. Precision measures the accuracy of the model in identifying positive learning predictions and Recall is used to measure the ability of the model to identify all the relevant positive cases. F1-Score gives a weighted assessment of Precision and Recall, making sure of healthy performance measurement in the analysis of collaborative learning. Top-10 Accuracy checks whether the correct prediction is found in the top ten ranked outputs produced by the model is in Equation 5 to 9. These assessment measures can be used to evaluate how well the proposed DGNN structure performs to represent peer interactions, learning behaviour and predicting student performance. TP, TN, FP, FN consider as True positive, True Negative, False Positive and False Negative.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

$$Recall = \frac{TP}{TP + FN} \quad (6)$$

$$F1Score = \frac{2 * Precision * Recall}{Precision + Recall} \quad (7)$$

$$Top - 10\ Accuracy = \frac{Correct\ Prediciton\ in\ Top\ 10}{Total\ Predictions} \quad (8)$$

### 4.5 Model Training Results

In this research, an improved GAT model was used that was trained on a simulated collaborative learning network of students. The graph consisted of 2,300 student nodes and the weights of the edges were determined by the frequency and type of interaction and time slice δt=1 week. The Adam optimizer was used to train with a learning rate of 0.005, a batch size of 128 and 200 epochs.605.

### 4.6 Hyperparameter Tuning Results

**Table 4: Hyperparameter Tuning Results**

| Hyperparameter | Accuracy | F1-Score |
|---|---|---|
| Learning rate 0.001 | 0.87 | 0.85 |
| Learning rate 0.005 | 0.91 | 0.90 |
| Attention heads 4 | 0.89 | 0.88 |
| Attention heads 8[20] | 0.91 | 0.90 |

Table 4 indicates that the hyperparameter analysis indicates that the choice of both learning rate and attention heads are important in the performance of the developed DGNN model. With a learning rate of 0.001, the model converged to an accuracy of 0.87 and an F1-score of 0.85, which is relatively low in terms of convergence efficiency. When the learning rate was increased to 0.005, the performance of the model improved significantly, leading to an accuracy of 0.91 and an F1-score of 0.90, indicating a more efficient model optimization and higher learning rate. Likewise, the heads of attention effect demonstrated that 4 attention heads yielded an accuracy of 0.89 and an F1-score of 0.88 and a further increase in the number of attention heads to 8, enhanced the performance to 0.91 and 0.90 accuracy and F1-score respectively. The findings show that increased attention capacity enhances the model to understand complex patterns of peer interaction and collaboration in learning. On the whole, the best predictive performance of the DGNN framework was attained with a learning rate of 0.005 and 8 attention heads.

### 4.7 Prediction Results

**Table 5: Prediction Results**

| Model | Accuracy | F1 Score | Top-10 Accuracy |
|---|---|---|---|
| Deep Walk | 0.72 | 0.70 | 0.60 |
| Graph SAGE | 0.76 | 0.74 | 0.66 |
| GAT [20] | 0.91 | 0.90 | 0.79 |
| DGNN | 0.93 | 0.95 | 0.85 |

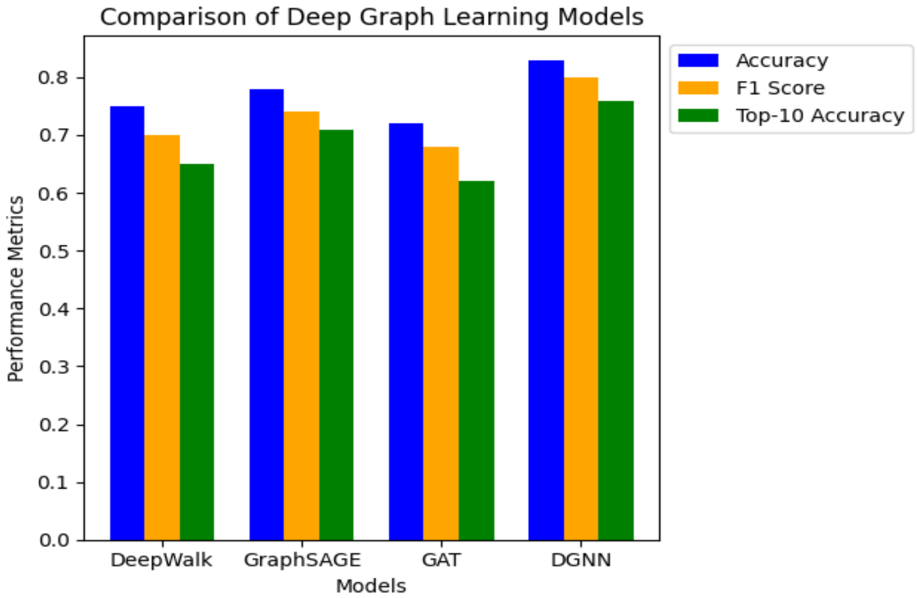

**Figure 3: Comparison of Deep Graph Learning Models**

Table 5 and Figure 3 demonstrate the prediction performance clearly indicates a steady increase in the performance of the models between Deep Walk and DGNN. Deep Walk shows the lowest values of 0.72 accuracy, 0.70 F1 score and 0.60 Top-10 accuracy meaning limited ability to capture complex relational patterns. GraphSAGE modestly improves with 0.76 accuracy, 0.74 F1 score and 0.66 Top-10 accuracy, indicating that it learns neighborhood aggregation better, but has limited representation learning. GAT shows a substantial performance improvement, with 0.91 accuracy, 0.90 F1 score and 0.79 Top-10 accuracy, indicating the usefulness of attention mechanisms in prioritizing significant graph nodes. DGNN has the highest overall accuracy of 0.93, F1 of 0.95, and Top-10 accuracy of 0.85 and it has good generalization and predictive power. In general, the findings imply that the application of advanced graph neural architectures can greatly improve the performance of the model, and DGNN offers the strongest and most balanced results in all the evaluation metrics.

### *4.8 Performance Comparison of Baseline Model With DGNN*

**Table 6: Performance comparison of Baseline model with DGNN**

| Moment | Categories | SVM | LR | SLFNN | GCN-Cosine | GCN-Pearson | MTGNN | DGNN |
|---|---|---|---|---|---|---|---|---|
| Week5 | Pass/Fail | 72.40 | 72.82 | 74.31 | 72.82 | 73.46 | 76.22 | 78.45 |
| | Pass/Withdrawal | 67.57 | 68.84 | 67.25 | 68.53 | 68.37 | 72.20 | 75.54 |
| Week 10 | Pass/Fail | 74.79 | 77.54 | 72.25 | 72.67 | 73.09 | 78.39 | 80.45 |
| | Pass/Withdrawal | 70.49 | 72.57 | 75.28 | 74.64 | 75.44 | 76.40 | 80.52 |
| Week 15 | Pass/Fail | 74.58 | 76.27 | 73.73 | 75.64 | 76.69 | 79.24 | 82.45 |
| | Pass/Withdrawal | 74.00 | 74.80 | 72.41 | 73.68 | 72.57 | 77.67 | 80.52 |
| Week 20[23] | Pass/Fail | 79.02 | 78.60 | 74.15 | 78.81 | 77.97 | 80.72 | 84.45 |
| | Pass/Withdrawal | 77.35 | 78.31 | 74.32 | 79.11 | 79.27 | 82.30 | 85.45 |

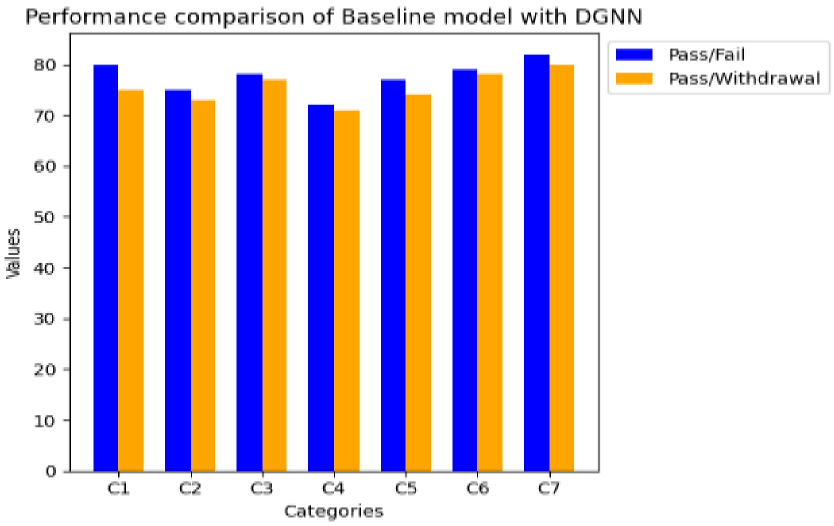

**Figure 4: Performance Comparison of Baseline Model with DGNN**

Table 6 and Fig 4 show the Weeks 5, 10, 15 and 20 performances of both the baseline models and the proposed DGNN model under Pass/Fail and Pass/Withdrawal classes reveal that the DGNN model obtained the best performance in terms of classification. In Week 5, DGNN achieved higher accuracies of 78.45% and 75.54% than the traditional machine learning models, including SVM, LR, and SLFNN, as well as graph-based methods, including GCN-Cosine, GCN-Pearson, and MTGNN. The performance gradually improved over time with the DGNN model achieving 80.45% and 80.52% in Week 10 and 82.45% and 80.52% in Week 15 in Pass/Fail and Pass/Withdrawal respectively. The overall results were the best in Week 20 with 84.45 in the Pass/Fail category and 85.45 in the Pass/Withdrawal category, which means that DGNN has high learning ability and ability to model collaborative interaction. Even though the performance of the MTGNN was also competitive with the base models, the results of the model were lower than that of DGNN at all the evaluation periods. The results affirm that the suggested DGNN model has excellent predictive accuracy and a higher ability to capture peer-learning connections in collaborative learning contexts.

### *4.9 Ablation Study Analysis*

**Table 7: Ablation Study Analysis**

| Model Configuration | Accuracy | F1-Score |
|---|---|---|
| Baseline Model (No GNN) | 0.74 | 0.72 |
| GNN Only | 0.87 | 0.85 |
| GNN + Temporal Features | 0.89 | 0.88 |
| GNN + Attention (GAT) | 0.91 | 0.90 |
| Full DGNN Model (Proposed) | 0.93 | 0.95 |

Table 7 presents the metric analysis indicates a strong and steady upgrading in performance as various components are incorporated in the model. The graph-based base model achieves the lowest scores of 0.74 and 0.72 in terms of accuracy and F1-score, respectively, which means that it is not as effective in learning intricate relationships in collaborative learning settings. The performance increases significantly to 0.87 accuracy and 0.85 F1-score when Graph Neural Network (GNN) is introduced, indicating that relational learning can be useful in modelling student interactions better. Further improvement can be seen with addition of time characteristics with the model gaining an accuracy of 0.89 and an F1-score of 0.88 showing how crucial it is to consider time variations in the learning behaviour. The further improvement of the performance to 0.91 accuracy and 0.90 F1-score with the addition of the attention mechanism is because the mechanism enables the model to pay more attention to the more relevant and influential interactions within the graph. Lastly, the entire DGNN model shows the highest learning rates of 0.93 accuracy and 0.95 F1-score, which proves the integrative learning of graphs, temporal dynamics, and attention mechanisms, is the most effective when used in collaboration learning in peer education.

## 5. Conclusion

The paper suggests Deep Graph Neural Network (DGNN)-based model to study the context of collaborative learning within peer education settings by solving the shortcomings of conventional assessment strategies to capture complex and dynamic student interactions. The primary advantage of this study is that it can model students as nodes and their interaction as weighted edges, which will allow it to effectively represent peer influence, the strength of collaboration, and learning behaviour. To learn relational dependencies, changing interaction patterns, and significant peer influences in a structured learning setting, the methodology combines graph representation learning, temporal feature modelling and attention mechanisms. The dataset comprises 2300 student nodes and interaction-based edges with a weekly time window in order to capture the learning dynamics over time, a realistic modelling of learning behaviour in education. The results of experiments demonstrate a steady performance increase in all model configurations. Accuracy and F1-score of the baseline model are 0.74 and 0.72 respectively, and with Graph Neural Networks, the model reaches an accuracy of 0.87 and F1-score of 0.85. The use of temporal features also enhances the performance to 0.89 accuracy and 0.88 F1-score, whereas the attention-based GAT model attains 0.91 accuracy and 0.90 F1-score. The optimal DGNN model suggested is the full model with the highest accuracy of 0.93 and F1-score of 0.95, which shows the best predictive performance and learning representation. The findings affirm that the incorporation of graph learning, temporal dynamics, and attention mechanisms can play a significant role in aiding collaborative learning analysis. The future research could be based on real-time learning analysis, multimodal data integration, and privacy-preserving graph learning to enhance scalability and real-world application in various educational systems.

### *Declaration*

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Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request

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