GNN-LS: A Learning Style Prediction in Online Environments using Graph Neural Networks

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Prediction of learners' learning styles in online environments has several advantages, including steering learners on the proper path, motivating and engaging them while learning, and improving their learning results. It also helps instructors in the formation of personalized resource recommendations. As a result, predicting learners learning styles is necessary to aid in the personalization process. Existing approaches use either conventional or automatic approaches for learning style identifications. However, the large volume of data stored in online platforms has become a challenge in analyzing the behavior of learners and predicting their learning styles in the real world. Also, most of the existing approaches rely on a particular learning platform and can not be used in other platforms without technical assistance. In this paper, we propose GNN-LS, a new approach to identify and predict learners learning styles using a graph neural network. First, the graph embedding technique is used to capture the representation of learners and resources as a bipartite graph and encode them into low-dimensional representation. The encoded L-R sequences were given as input to the K-means clustering algorithm to identify and obtain labels as per FSLSM dimensions. Then, Graph neural network is trained to predict the learner's learning style in the real world. The GNN-LS technique can be applied in a variety of educational systems and adapted to fit a variety of learning style models. Extensive experiments are run using the 2015 KDD Cup public available dataset to demonstrate the capabilities of GNN-LS. 5.31-15.68% improvements are achieved across all four FSLSM dimensions in accuracy.

***Index Terms*—Learning style, graph neural network, FSLSM, learners behavior.**

I. Introduction

The need for personalization in online learning is becoming more and more crucial as learners have different needs and characteristics such as different backgrounds, abilities, motivations, and personalities. However, many online platforms ignore learners' individual needs and provide them with uniform resources and activities [1], [2]. Personalized learning can be accomplished through learning style detection, which is the most significant and is considered among the personality traits in online educational systems. Learning styles describe how students collect and process information based on their attitudes and behaviors [3]. Knowing the learners' learning styles based on their behavior in online platforms can help them improve their learning process in a variety of ways. For instance, it assists learners in improving their learning skills and achieving their learning objectives, directing them in the right direction, motivating and engaging them while learning, and reducing dropout rates by illuminating them to understand their learning styles and knowing their strong and weak points, which can help in making stronger insight when self-regulating their learning. Furthermore, it enables teachers to deliver more appropriate learning resource recommendations and convey knowledge through a variety of means, such as video, audio, text, and picture.

Manuscript received November 2, 2022; revised December 28, 2022.

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This work is supported by the Major Achievements Cultivation Project of Collaborative Innovation Center of Assessment toward Basic Education Quality at Beijing Normal University, China (2020-05-0034-BZPK01)

There have been significant research efforts in the literature on how to apply learning style in online learning, particularly in the field of learning style detection and prediction. Most existing approaches rely on recorded real-world data regarding learners' behavior and employ either data mining, machine learning, or deep learning algorithms to automatically detect learners' learning styles.

Learning styles are identified using either traditional or automatic approaches [4]. The traditional approach entails using a dedicated questionnaire to identify the learner's learning styles, with each of the learning style dimensions having its own set of questions [5]. Although the use of questionnaires is valid and reliable, it has several drawbacks. First, there is a lot of bias when learners fill out the questionnaire as it contains many questions. Second, it is time-consuming and relies on the learners' self-awareness in answering the questions. Thirdly, ignoring changes in the learner's learning style that may occur over time or during the learning process may result in providing learning resource that does not match the learner's style. As a result, detecting learners' learning styles can lead to less accuracy and make it difficult to use in online environments. To address these limitations, research has focused on an automatic approach to identifying the learner's learning style based on their behavior in online educational systems [6], [7], [8]. They employed various machine/deep learning techniques to predict the learner's learning style. The approaches have the potential to be more dependable and error-free, but the exponential growth of data makes it challenging to capture learners' behavior and predict their learning styles adequately. Moreover, the approach's accuracy are highly dependent on data availability and course features and is less adaptive when dealing with a wide range of subjects or when the behavior of learners changes.

To overcome the limitations and acquire an efficient learning style approach under large-scale data. We have to automatically capture and learn the behavior features from the recorded activities and interaction of learners with various resources using graph representation learning [9], [10]. In this paper, we propose a learning style prediction approach based on graph neural networks for online platforms. In this approach, we have automatically encoded the learner-resource (L-R) sequence from their recorded behavior, then an unsupervised learning algorithm is used to identify and obtain labels according to chosen learning style model of the Felder-Silverman learning style. After that, the graph neural networks (GNNs) model is trained to predict the learners learning style of new or existing sequences of the learner. The GNNs model is a neural network that can be applied to graphs and has the ability to solve node classification problems. The contributions of the paper are outlined as follows.

1) We proposed a model that considers the growth of Felder-Silverman learning styles and the encoded learner's sequence, which is generated from an L-R bipartite graph describing the behavior of learners in order to predict learning styles.
2) A novel GNN-LS model is proposed, which makes use of a GNNs model for node classification problems to predict learners learning styles of new learners while also taking into account the eight categories of Felder-Silverman learning style models.
3) Extensive experiments using the real-world 2015 KDD-Cup dataset reveal that the proposed GNN-LS effectively classifies the learner's preferred method of learning in terms of its accuracy. Compared to the baseline models and an existing approach, the proposed GNN-LS model performs exceptionally well.

The rest of the paper is structured as follows. Section 2 contains background information on learning styles as well as a description of current research on automatic approaches to learning style identification. Section 3 describes the proposed approach for identifying learning styles. Section 4 presents the evaluation of the proposed approach. Finally, Section 5 concludes this works and suggests future directions.

II. Related Work

In this section, we first introduce some background information on learning styles and then the existing approaches for automatic learning styles prediction.

A. Learning Style

Learning styles describe the attitude and behavior of learners when they are learning and they have an impact on how learning resources are distributed, used, and initialized [4]. In online education, learning styles are significant because they can direct learners in the right direction, improve their learning outcomes in a variety of ways, and help instructors give more personalized recommendations. The learning style concept was developed on the premise that each learner learns in their own unique manner and personal style. Some learners learn best when information is presented visually, while others prefer verbal instruction. Various learning style models have been developed by various psychologists based on various characteristics such as learner behavior, psychological circumstances, cognitive styles, and even environments [5]. David Kolb's model, Fleming's VARK model, Gardner's theory, Honey and Mumford's model, Felder-Silverman's learning styles (FSLSM), and so on are a few examples. These models aid in the development of instructional tools based on the preferences, experiences, and learning styles of the learners.

Table I. Dimension and Categories of FSLSM

Learning Dimension	Learning Categories
Input	Visual
	Verbal
Processing	Active
	Reflective
Perception	Sensitive
	Intuitive
Understanding	Sequential
	Global

For various reasons, the Felder-Silverman learning style model (FSLSM) was chosen from among the existing learning styles theories [11]. First, it is the most widely used in online education and employs an experimental approach to demonstrate the model's reliability and validity. Secondly, the model has many advantages as it describes learner behavior in greater detail than other models. Thirdly, the model categorizes learners' learning styles into four dimensions as shown in Table. I: input (visual/verbal), processing (active/reflective), perception (sensitive/intuitive), and understanding (sequential/global) each of which is comprised of two learning styles that describe how learners collect, process, and comprehend information based on their behavior in online systems [5], [10], [12].

Input dimension: The visual/verbal (V/V) dimension describes learners' input preferences. Visual learners retain information better when it is presented as a graph, chart, or image whereas verbal learners are more likely to retain information that is written.

Processing dimension: Active/reflective (A/R) distinguish between active and reflective information processing. Active learners improve their learning by engaging in a group discussion or explanation of a learning resource. On the other hand, the reflective learner prefers to contemplate and reflect on a learning resource independently or in a small group.

Perception dimension: Sensitive/intuitive (S/I) dimension describes how learners interpret information. Sensitive learners prefer to learn facts and concrete thinking and are more interested in finding well-established methods for solving problems. Whereas learning intuitively involves conceptual thinking and tends to work quickly, as well as finding new innovations and dispising repetition.

Understanding dimension: The sequential/global dimension describes how the learners prefer to organize information. Sequential learners typically follow linear reasoning processes and are more inclined to learn through small steps. Global learners tend to learn in large leaps and build their own cognitive map of the content through a holistic reasoning process.

B. Existing Automatic Learning Style Prediction

In the literature, various ways for identifying and predicting learning styles have been offered, with research based on various learning style models, and the results define whether a learner is classified as visual/verbal, active/reflective, sensitive/intuitive, and sequential/global. According to [13], [14], two approaches for the automatic detection of learning styles that might be used are literature-based and data-driven strategies. The researchers demonstrated numerous artificial intelligence algorithms to automatically detect learning.

The literature-based approach often leverages learners' behavior to gain insight into their learning behavior and then applies a simple-rule-based method to identify their learning styles based on the number of patterns matched. This approach is more generalized and can be used with data from any course. This method has been utilized by several researchers to identify learners learning styles [15], [16], [17], [18], [19]. However, the approach may have inaccurate because assessing the importance of different cues when determining learning styles is challenging. Furthermore, the approach cannot adjust to changes in learners' learning styles because it is so close to the conventional approach

The data-driven approach, on the other hand, aims to construct a model that resembles the index of learning style (ILS) questionnaire. It uses the learners' behavior data to build models for the prediction task. Most of the existing approaches for learning style prediction build a model from the extracted learners' behavior data to build a classifier such as a Decision tree (DT), Bayesian network (BN), Artificial neural networks (ANN), and other models. For instance, various methods in the literature employ the use of a DT classifier as the most frequently used classification approach to predict the learning styles of learners [20], [21], [22], [23], [24], [25]. Bayesian network (BN) and Naïve Bayes (NB) are other categorization algorithms used to forecast the learning styles of the learners [26], [27], [28], [29], [30]. These classifiers can quickly and accurately predict the likelihood of a given sample belonging to a specific class, especially when working with enormous datasets. [31] suggested using dynamic BN to detect learning styles. A neural network is another classifier used for the prediction task, such as [32], [33], [34], [35], [36], [37], [38], [39]. The NN is a machine learning algorithm that contains a set of connected input/output units, where each connection (neuron) is assigned a weight.

Furthermore, some recent work combined different machine learning techniques such as genetic algorithms, support vector machine (SVM), Logistic regression, K-nearest Neighbor, random forest (RF), BN, NN, NB, and DT for predictions of learners learning styles [2], [14], [40], [41]. For instance, [40] considers four machine learning techniques for the experiments of the prediction tasks, and the result obtained shows that the decision tree (DT) achieved accuracy across the three dimensions of FSLSM.

In addition, other approaches used a hybrid method to predict learners learning styles, especially when the extracted learner behavior data does not have labels. In these approaches, a clustering algorithm is applied to obtain labels according to the learning style theory selected, then a classifier is trained for the prediction tasks. [40], [42], [43], [44], [45], [46] are among the proposed approaches that use a clustering algorithm to obtain labels and built a classifier for the prediction tasks.

Table II provides a summary of some existing hybrid approaches and their shortcomings for learning style predictions. Most of the papers summarized adopted the use of FSLSM. Previous approaches have employed various approaches for learning style prediction. However, the approach's accuracy is highly dependent on data availability and course features and is less adaptive when dealing with a wide range of subjects or when the behavior of learners changes. Also, they are designed to work only on a particular learning platform or the education system, only a few can be re-used without technical assistance in other platforms or educational systems. inspired by the existing problems of hybrid approaches, we proposed the GNN-LS approach.

III. The Proposed GNN-LS Approach

In this section, we describe in depth the GNN-LS that was proposed to predict a learner's preferred learning strategy. Fig. 1 is a diagrammatic representation of the suggested workflow. In this work, we propose the uses of graph representation learning and machine learning algorithm to build a model that enables to detection and predict the learning style of learners.

The first step is using graph-based analysis to collect the recorded learner's behavior and modeled it as a bipartite graph. This gives us a distinct set of learners, a set of learning resources, and their structural weight relations describing how often and for how long each resource is used by the learner. Then the constructed L-R bipartite graph is encoded into a low dimensional representation using graph representation learning techniques for subsequent machine learning tasks. In the experiments, 5069 sets of learners and 7 sets of learning resources were recorded from the used dataset.

After encoding the L-R bipartite graph into a low-dimensional representation (encoded L-R sequences). Our aim is to detect and classify learners learning styles according to the selected FSLSM by assigning the learning style dimension to each encoded learning resource. Despite the fact that the encoded L-R sequence has no labels, the proposed GNN-LS is broken down into two modules: The learner clustering module and the learning style prediction module. In the learner clustering module, the encoded L-R sequences must be transformed to the input of the clustering algorithm in order to assign a label to each sequence according to the FSLSM dimension. In the learner style prediction module, the labeled sequence obtained was used as a training set in order to predict the learners learning styles for a new learner, or the next sequence of learners.

A. Learner Clustering Module

During the learner clustering module, we first determine the relationship between the encoded learning resource features

Table II. Some current hybrid methods for learning style prediction

Papers	Clustering Algorithm used	Prediction Algorithm used	Descriptions
Hidayat et al. [45]	K-means	Naive Bayesian	Prediction models already in use were not used to gauge accuracy.
Hmedna et al. [40]	K-means	DT, RF, KNN, and NN	Does not consider perception dimension of FSLSM
Kolekar [42]	Fuzzy C-means	Gravitational Search based Back Propagation Neural Network (GSBPNN)	There was no evaluation of the method's efficacy in light of prior research.
Aissaoui et al. [44]	K-means	Naive Bayes	The method only looks at one course in their trail.
Zhang et al. [46]	Restricted Boltzmann machine (RMB)	Back Propagation (BP)	The strategy was put into action, however it was not evaluated in comparison to other strategies.

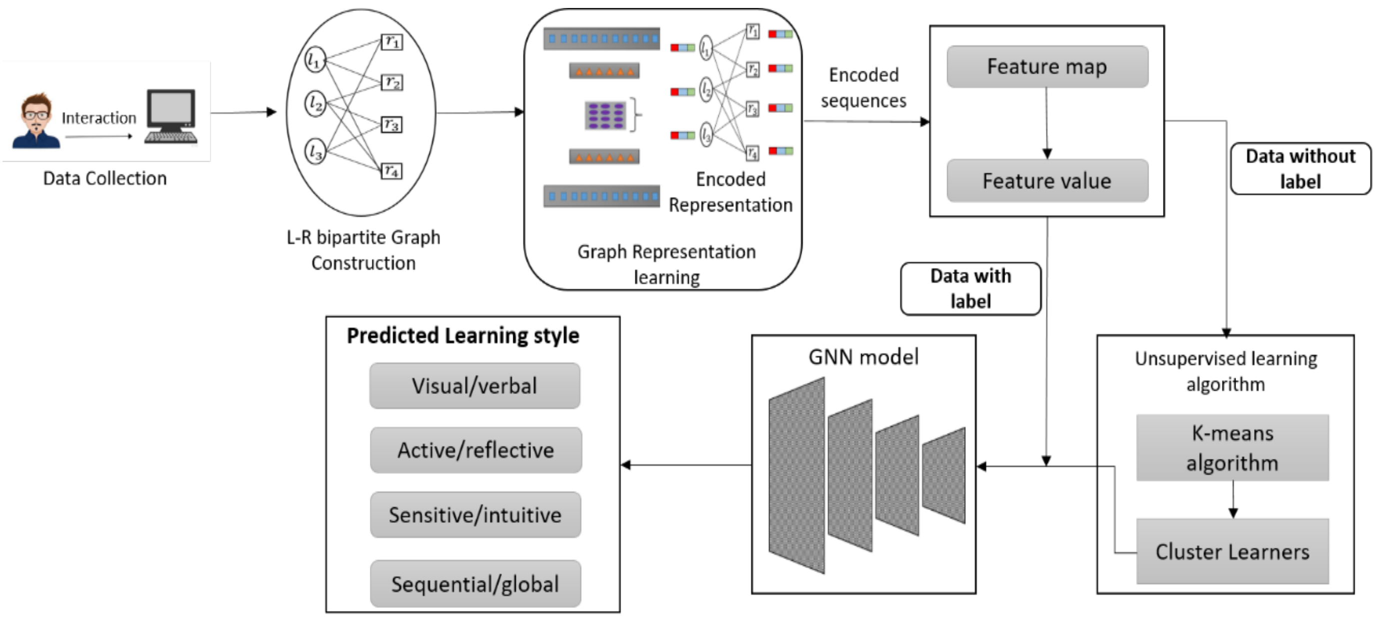


Figure 1. The proposed GNN-LS approach overview for learning styles prediction

that support the description of FSLSM dimensions. The resulting features were used as input to the clustering algorithm to assign labels according to the FSLSM dimension. In this paper, we use a k-mean algorithm to generate labels for a variety of reasons. First, it is one of the most common and intuitive unsupervised clustering algorithms for grouping data in machine learning, and the very first thing partitioners apply when solving clustering tasks. Using this technique is very easy and straightforward to classify unlabeled datasets, and it can be applied to graphs as well.

1) Mapping the Encoded Learning Resources with FSLSM dimensions

The learner's actions and interactions with learning resources while taking online courses were viewed as L-R bipartite graph, then uses a GRL technique to automatically encoded the feature into a fixed-length vector. The initial proposal is described in detail in the study by [9], [10]. The encoded L-R bipartite graph contains a set of learners, a set of learning resources, and their vector representations. Based on the mapping table presented in our previous work [9], which maps each online learning resource as per FSLSM, we obtained Table III, where the resulting is considered as input to the K-means clustering algorithm.

Table III. Mapping the encoded learning resources with FSLSM dimensions

FSLSM Dimensions	Encoded Learning Resources
Input (Visual/Verbal)	Video, image, audio, charts, announcement, PDFs, email
Processing (Active/Reflective)	Discussion forum, exercise, wiki, access, email, chat
Perception (Sensitive/Intuitive)	assessment, examples, exam revision, access
Understanding (Sequential/Global)	Exam revision, navigation,page close

2) K-means clustering algorithm

In this section, the resulting feature associated with each FSLSM dimension was given as input to the K-means clustering algorithm. For each FSLSM dimension, the sequence is classified according to each FSLSM category where the resulting features are given as input to the k-means algorithm.

The initial stage of the algorithm is to determine the number of clusters (K). In this paper, we use $K = 2$ according to the FSLSM dimension as shown in table 2, which is the most optimal way for separating two FSLSM dimensions. The next

Table IV. Summary of the used concepts and notations used

Notations	Concepts
$G = (L, R, E)$	The L-R Bipartite Graph
L	The set of learner's node
R	The set of resource's node
E	The set of edges
l_i	A node and $l_i \in L$
r_j	A node and $r_j \in L$
X	Node Feature
K	The node features
A	The adjacency matrix
I	Identity matrix
d	The input feature dimension
H	The node representation

step is the centroid determination which is done based on the selected K random dataset. Then the algorithm calculates the euclidean distance for every learner l_i to the initial centroid $k(c_k)$ and assigns the learner to the closest centroid. The algorithm uses different iterative computations to re-calculate the euclidean distance from the centroid for each learner until convergences are stabilized. The output of the clusters can be used to predict the learners learning styles.

We use jupyter notebook, a python programming language in order to perform the k-means algorithm.

B. Learning Style Prediction Module

The process of predicting the learning styles of learners involves labeling the encoded L-R bipartite graph as per FSLSM dimensions and building the classification model. After labeling the latent representation Z with FSLSM categories using the K-means algorithm. All the latent representation sequences can be used to train the classification algorithms. to classify the latent representation sequence, a Graph neural network is used. In the following paragraphs, we will give a comprehensive introduction to the GNN algorithm and explain how it can be used to forecast students' preferred methods of instruction.

1) Overview of the GNN

In this section, we first define some key terms and give a standard notation used in the paper before explaining the detailed overview of the GNN model. we present a number of notations summarized in Table IV

Problem definition: Let's start with a problem statement for GNN-based node classification, in which we learn the encoded L-R bipartite graph. let $G = (L, R, E)$ represents the latent representations (encoded L-R graph) where L and R are the learner and resource nodes and E represents their weight relations. There is an Adjacency matrix denoted by $A = R^{(N \times N)}$, where N is the total number of nodes, and an encoded feature vectors denoted by $X = R^{(N \times C)}$, where C is the number of features for each node. The aim of the GNN model is to effectively learn the vector representation of the encoded L-R graph for each FSLSM dimension by combining the structural information with the vector representations for node classification.

Graphs have recently attracted a lot of interest in the machine learning community because of their versatile expressiveness. Graphs or networks are used in many disciplines to describe real-world problems, such as those encountered in recommender systems (User-item interaction), social networks (Friendship network), and biological science (protein-protein interaction) [47]. Graph learning has become the most successful deep learning technique on a graph today in the artificial intelligence research field, despite the widespread success of classic deep learning models like artificial neural networks (ANNs), conventional neural networks (CNNs), and recurrent neural networks (RNNs) with euclidean data like text, images, and sequences. In these cases, the concepts of deep learning on graphs come into play, as the graph structure, which stores the structural data's complex pairwise interactions, can be intuitively presented as the best way to convey the problem. Learning graph embeddings that account for structural and neighboring information have seen a meteoric rise in popularity in recent years, particularly in the data mining and machine learning community. Since graph embedding techniques are among the most effective methods for automatically determining the representation needed from a sizable network's worth of data in order to perform machine learning tasks, many different kinds of graph embedding methods have been proposed in the literature [48], [49].

Currently, Graph neural networks (GNNs) is the most effective learning framework for a wide range of application domains, including recommender systems, social networks, and natural language processing, among the existing deep learning techniques on graph available from the research community [50], [51]. Many approaches utilized the use of GNN to achieve remarkable performances in some well-known domains. In this paper, the GNN model is used for a number of reasons: First, the GNN model is superior because of its ability to manage both vast and complicated networks by making use of a non-euclidean structure to link information between nodes. Secondly, GNN is a subset of deep learning methods optimized for discovering connections in graph data and has given us a unique opportunity to learn about large network data because they use the natural connections between things that can be modeled as graphs. The main purpose is to learn the embedding that includes information about its surroundings, and the information can be collected from the graph-structured data. The embedding can be used to solve problems like labeling nodes and predicting nodes and edges. In addition to its exceptionally powerful expressive skills and easy access to computations and data, GNN model has the potential to solve a wide range of machine-learning problems, such as node classification, link prediction, and graph classification. In this work, we only look at how to use GNNs to classify nodes. In the node classification task, the model has to figure out the labels of the samples (which are shown as nodes) based on the labels of the nodes around them [49].

In the GNN model, a final embedding is determined for each node through the application of a linear transformation with a trainable weight matrix and feature propagation techniques to collect node neighborhood information. The core concept underpinning GNN is that node representations can be improved upon by fusing the nodes' own representations with those of their surroundings in an iterative process. With the GNN framework, we begin with the node representation $H^0 = X$, then at the k^{th} layer, where $k = 1, 2, \ldots k$, we have two crucial operations:

Aggregate: The job of the aggregate functions is to collect data from each node's neighbors and use it as a whole.

$$a^k_{(L,R)} = AGGREGATE^K\{H^{k-1}_{l,r} : l \in N(L) and r \in N(R)\} \tag{1}$$

Combine: This function updates the node representations by combining the aggregation function with the current node representations.

$$H^k_{(L,R)} = COMBINE^K\{H^{(k-1)}_{(l,r)}, a^k_{(l,r)}\} \tag{2}$$

Where $N(L)$ and $N(R)$ represent the set of neighbors for the l^{th} and r^{th} nodes. the H^K represents the final node representation layers.

Next, the node classification algorithm is used as a case study to predict the node labels $y_{(l,r)}$ using softmax functions based on the obtained node representations.

$$y_{(l,r)} = Sof\hat{t}max(WH^T_{(l,r)}), \tag{3}$$

where $W \in R^{(|M| \times F)}$, $|M|$ denotes the number of labels in the final product space.

The model is trained by minimizing loss functions, given a set of labeled nodes as follows.

$$O = 1/n_m \sum_{i=1}^{n_m} loss(\hat{y}_i, y_i), \tag{4}$$

Where y_i represents the ground-truth label of each node i, n_m denotes the number of nodes with labels, and $loss(.,.)$ represents the loss function, such as the cross-entropy loss function. Backpropagation can be used to optimize the whole neural network by making the objective function O as small as possible.

The most used variant of GNN in the literature includes convolution, attention, message passing, graph pooling, and recurrent. In this paper, we utilized graph convolution networks (GCNs) for node classification to build a model that learns the representation of the encoded L-R sequence. The model will learn the node's hidden representation not only based on its own features but also its neighboring node's features according to each FSLSM dimension.

Graph Convolution Networks

The GCN is the most frequently used GNN architecture in the literature due to its simplicity and effectiveness in various application domains and tasks [52]. In each layer, the node representation is updated according to the following propagation rules

$$H^{k+1} = \sigma(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}H^kW^K), \tag{5}$$

Where $\tilde{A} = A + I$ represents the encoded L-R sequences adjacency matrix with self-connection allowing for the integrations of node features when updating the representations of nodes. $I \in R^(N \times N)$ denotes the identity matrix. $\tilde{D}$ represents the diagonal matrix with $\tilde{D}_{ij} = \sum_j \tilde{A}_{ij}$. $\sigma(.)$ is the activation function like $ReLU$ and $Tanh$. The $ReLU$ activation function, which is defined as a layerwise linear transformation matrix that will be trained during the optimizations, is commonly utilized. It can be written as $ReLU(x) = max(0, x)$. $W^k \in R^{F \times F^1}$, where the F,F^1 are the dimensions of node representations in the k^{th} layer.

Equations 1 and 2 can be further analyzed to reveal the GCN-defined aggregate and combine function. Node i's updating equation can be rewritten as follows.

$$H^k_i = \sigma(\sum_{j \in \{N(i)Ui\}} \frac{\tilde{A}_{ij}}{\sqrt{\tilde{D}_{ii}\tilde{D}_{jj}}} H^{k-1}_j W^k), \tag{6}$$

$$H^k_i = \sigma(\sum_{j \in N(i)} \frac{\tilde{A}_{ij}}{\sqrt{\tilde{D}_{ii}\tilde{D}_{jj}}} H^{k-1}_j W^k + \frac{1}{tildeD_i} H^{k-1}_i W^k), \tag{7}$$

2) GNN for Learning Style Prediction

After going through the process of being labeled by the k-means clustering algorithm on the input-encoded L-R sequence in accordance with the FSLSM dimension. The encoded L-R sequences were utilized to train the GNN models for node classification, which were then used to predict students' preferred learning strategies for the new or next sequence across the eight categories of FSLSM. In this paper, we used GNN to classify the sequences. The encoded sequences were given as input to the GNN model in order to improve the accuracy of the existing learning style prediction approaches. The GNN model was treated as a node classification problem for many reasons. First, in recent years, the GNN has emerged swiftly to deal with graph-structured data, which cannot be easily represented by conventional deep-learning approaches built for Euclidean data. Second, it is the most powerful model for dealing with complex structures, and it has been widely applied in a variety of applications and domains such as modern recommender systems, computer vision, natural language processing, program analysis, anomaly detection, and so on. However, it has not been used for learning style prediction based on our knowledge. GNN can also be utilized for downstream machine-learning tasks such as node classification, link prediction, and graph categorization.

The GNN model is utilized whenever there is a need for a node classification task as discussed before. Node classification is the most significant task in GNN, and it has been widely researched for the purpose of solving problems related to graph semi-classification. We look at the problem of node classification on the encoded L-R sequence, which stands for the latent representation of the created L-R bipartite graph $G = (L, R, E)$, where L and R stand for the nodes of learners and resources, respectively, and E stands for the edge. The edge between the nodes $l \in L$ and $r \in E$ is denoted as $(l, r) \in E$. $A \in R^{(NN)}$ represents the weight adjacency matrix with a loop of edges. To simplify, $X = \{x_1, x_2, \ldots, x_N\}$ signify the encoded feature vectors of nodes, and $Y = \{y_1, y_2, \ldots, y_N\}$ as the labels of all the nodes will be used to train models.

The feature values related to each FSLSM dimension are given as input to the GNN model. GNN is considered as a function $f(A,X)$ conditioned on node features X and adjacency matrix A, then aggregates the features of two hops of neighbors and output Z. Finally, the GNN algorithm classifies the learning styles of learners according to each FSLSM dimension such as visual/verbal, active/reflective, sensitive/intuitive, and sequential/global as shown in the proposed GNN-LS framework for learning style prediction.

IV. Experimental Results and Performance Analysis

In this section, we describe the datasets used for the experiment first and the evaluation metrics for performance evaluation. Then the parameter setting for the experiment as well as the result analysis and discussion. Finally, we compare the performance of the proposed GNN-LS approach with the state-of-the-art approaches.

A. Datasets Description and preprocessing

To evaluate the efficiency of the proposed GNN-LS approach, we used the same dataset that has been used for evaluating GRL-LS [9]. The dataset includes information on course enrollment, dropout rates, and behavior data records. The process used to acquire and process the behavioral data from MOOC is described as follows. The dataset was gathered from over 1,700,000 registered users around the world from various universities. The KDD Cup hosted the courses between December 2013 to September 2014 and some of the resulting data has been accessible since 2015.

Table V. The information about the constructed Bipartite Graph data

Dataset	KDD Cup 2015
Learner nodes	5069
Resource nodes	07
Edges	27,163

The dataset was transformed into a bipartite graph representing the set of learners, the set of learning resources, and weight relations. Following that, learners' sequences were extracted and encoded into latent representations for subsequent machine-learning tasks. The encoded behavior data was described in detail in Table V

B. Parmetre Settings

In this subsection, the proposed GNN-LS is implemented using the Keras library. All the model's parameters were initialized using an adam optimization algorithm. A mini-batch size of 256 was used and the number of epochs in $\{50, 100, 200\}$. the learning rate is set to 0.001, and the hidden unit to [32, 32]. We set the GNN layers to 2 with a dropout rate of 0.5 to overcome overfitting. The data was split into two by choosing 80% for the training sets and 20% for the testing sets. We use accuracy as the most frequently used evaluation metric to test the performance of the proposed GNN-LS approach.

C. Experiment and Results Discussion

We conducted an experiment to verify the effectiveness of the proposed approach. The experiment consists of two parts: First, a clustering experimental procedure was utilized to identify and get labels in accordance with the chosen learning style model of FSLSM. Second, we use the clustering result to test the GNN algorithm's ability to classify the new sequences of the existing or new learner according to FSLSM categories.

In the clustering part, using the encoded L-R sequences and k-means clustering algorithm, we classify learners into a group and get labels based on FSLSM categories. The feature values acquired by mapping the learning resources to the FSLSM dimensions are used to calculate the center values for each cluster. Given that k=2 is the best way to partition two FSLSM dimensions, we apply the algorithm to all possible FSLSM dimensions. The outcomes of the k-means algorithm can be seen in Table VI.

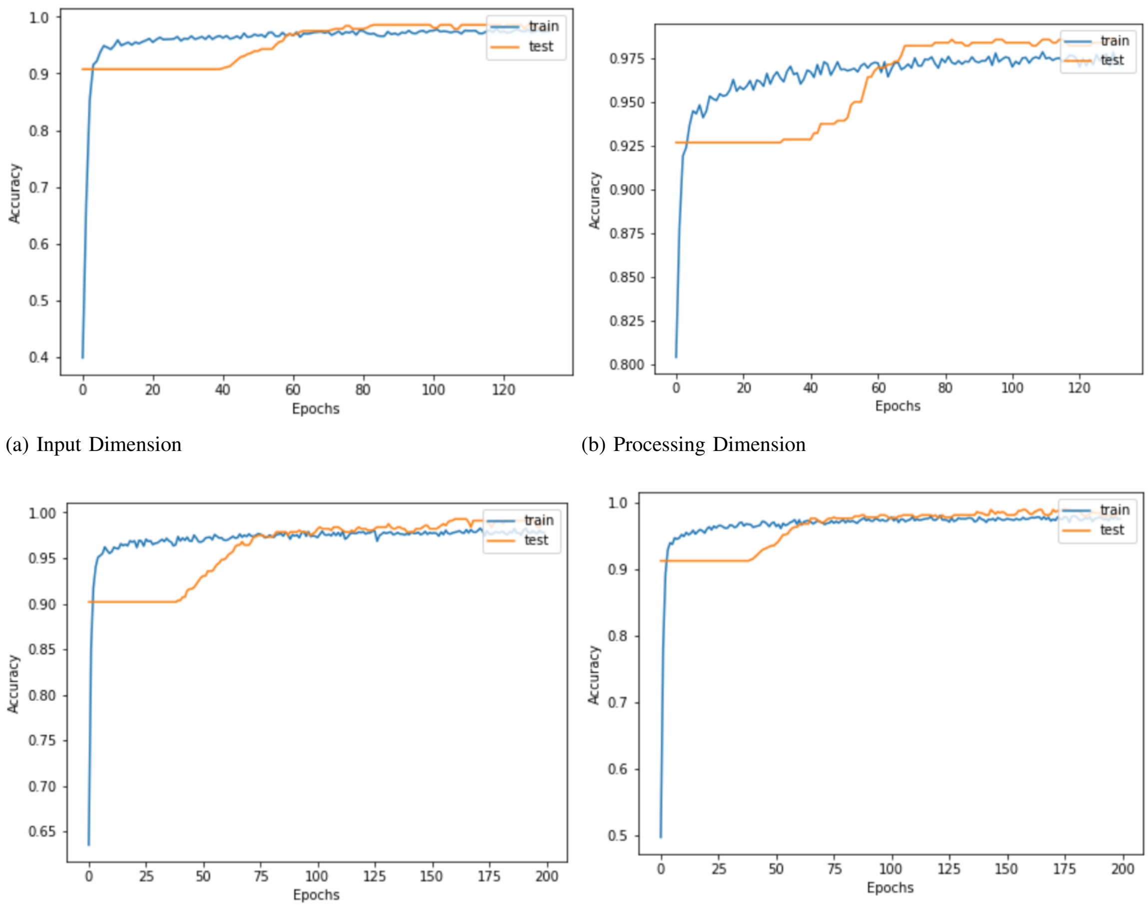
Table VI. The Clustering results

FSLSM Dimension	**FSLSM Categories**	**No. of Learner**
Input	Visual	4,208
	Verbal	445
Processing	Active	4,208
	Reflective	445
Perception	Sensitive	4,192
	Intuitive	436
Understanding	Sequential	497
	Global	4,572

We can see from Table VI that there is a clear disparity in the total number of students across the various dimensions. The mapping has led to this conclusion since we now only choose students who engage with similar aspects in the FSLSM.

In the second part, the results of clustering were fed into the GNN models to test how well they could classify the sequences of the existing and new learners for each FSLSM dimension. The model is executed with a different number of epochs for each FSLSM dimension. The number of epochs determines the number of iterations that the GNN models will work across the entire training set. Fig. 2 illustrates the GNN-LS model's accuracy for learning style prediction for each FSLSM dimension. Here, we train the model with accuracy as the evaluation matrix to access the quality of the classifier at a different number of epochs. We chose 50, 100, and 200 epochs with various accuracy levels. The proposed GNN model is comprised of kernels in each of the graph convolutional layers. For each dimension of FSLSM as can be seen from Fig. 2, the accuracy obtained increases as the number of epochs increases. This indicates using the optimal number of epochs chosen, the proposed approach performs well in all the FSLSM dimensions.

During the experiments, the model is trained by minimizing the loss function along each dimension of the FSLSM. To evaluate the performance of the proposed GNN-LS approach to represent a given dataset, we employ categorical cross-entropy, the most popular loss function for multi-class node



(a) Input Dimension

(b) Processing Dimension

(c) Perception dimension

(d) Understanding dimension

Figure 2. GNN-LS model's accuracy for each FSLSM dimension

classification issues. It is used to quantify the degree to which two probability distributions differ from one another, it is an essential component of any statistical model. Using 200 epochs, Fig. 3 depicts the loss function produced in each FSLSM dimension. For each FSLSM, we can see that the prediction's output drops. It's clear that the proposed works well in every facet of the FSLSM. According to the published works, the loss function performs better when the anticipated values are lower, and the loss function results in a larger value when the predictions are badly wrong. If you're trying to improve your model by tinkering with the parameters of your algorithm, the loss function will show you where you stand.

D. Performance Comparison

First, we compare the performance of the suggested GNN-LS approach to the state-of-the-art baseline model to gauge its efficacy. We then evaluate our results in relation to the previously established method for detecting learning styles, also employing this dataset.

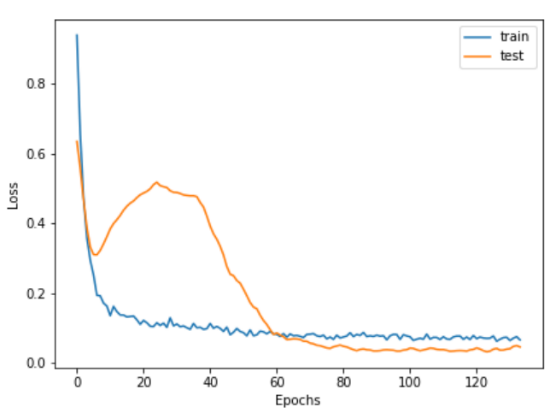
1) Performance Comparison with the Baseline Model

TableVII displays the accuracy achieved in comparison to the baseline neural network at various epoch counts [50, 100, 200]. In Table VII, we can see how the accuracy of the baseline model changes over time in relation to the various iterations.

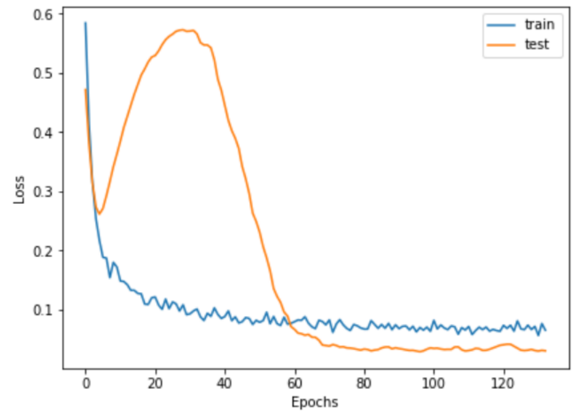
Table VII. Performance comparison with the baseline model in terms of accuracy for different numbers of epochs

Models	**Learning Style**	**Number of Epochs**		
		50	100	200
NN	Vis./Ver.	93.95%	94.46%	98.34%
	Act./Ref.	91.97%	96.65%	98.05%
	Sen./Int.	90.55%	96.11%	98.33%
	Seq./Glo.	94.49%	96.30%	98.50%
GNN-LS	Vis./Ver.	94.38%	97.01%	98.34%
	Act./Ref.	93.70%	97.94%	98.33%
	Sen./Int.	91.77%	98.33%	98.87%
	Seq./Glo.	94.99%	96.89%	99.00%

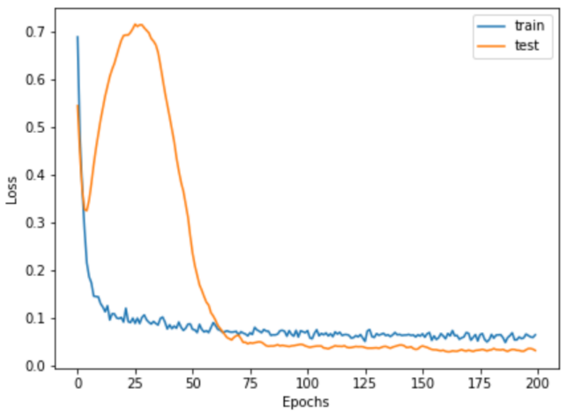
For this experiment, we have decided to use a different number of epochs. The feedforward neural network serves as the standard against which the accuracy performance is measured. At each iteration, the GNN-LS model outperforms the baseline model on every facet of FSLSM. By increasing the number of epochs, we can see that the accuracy of the model also grows. Moreover, the execution time of the GNN-LS grows longer as the number of epochs grows larger.



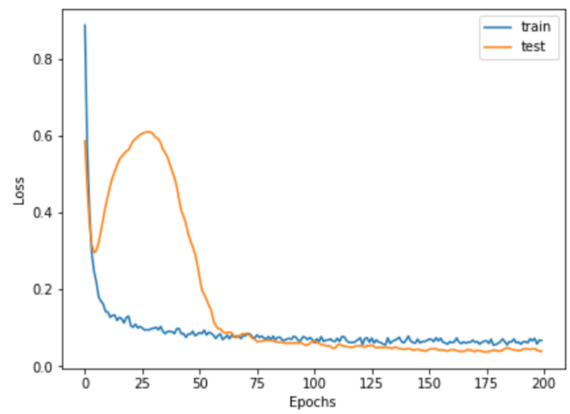
(a) Input Dimension



(b) Processing Dimension



(c) Perception dimension



(d) Understanding dimension

Figure 3. GNN-Model's Loss function for all dimension of FSLSM

2) Performance Comparison with the Existing Approach

The purpose of this study is to examine how well different learning styles may be identified in different students. Accuracy and precision in learning style detection were determined using the GRL-LS technique [9]. In this study, we assess the performance against the existing GRL-LS approach with regard to accuracy, as the outcome of the GRL-LS approach has clearly presented the best result compared with the state-of-the-art approaches as shown in Table VIII

Table VIII. Performance comparison with the existing approach

Approach	FSLSM dimensions				
	Vis/Ver	Act/Ref	Sen/Int	Seq/Glo	Avg
GRL-LS	91.00%	93.00%	85.00%	84.00%	88.25%
GNN-LS	97.01%	97.94%	98.33%	96.89%	97.54%
% Improvement	6.60%	5.31%	15.68%	15.35%	10.74%

GNN-LS significantly outperforms the existing baseline model on accuracy. For each dimension of FSLSM, the GNN-LS accuracy scores for input, processing, perception, and understanding are 97.01%, 98.43%, 91.00%, and 90.37% respectively. The Seq/Glo dimension has the best improvement by 7.58% while the act/ref dimension has less improvement by 5.84%.

The effectiveness of the GNN-LS method is evaluated experimentally in terms of accuracy metric. As can be seen from Table 3, GNN-LS outperforms the NN-based model across all dimensions of the FSLSM, allowing it to serve as a useful benchmark. While GNN-LS performance decreases as the number of epochs decreases, it improves with more epochs while working with the given dataset. In contrast to standard NN models, the results show that the GNN model utilized here achieves excellent performance and is capable of efficiently classifying students. We also evaluate how well the GNN-LS performs in comparison to the current graph-based method of detecting learning styles. Comparable levels of performance were seen across all four dimensions of the FSLSM. This evidence suggests that the suggested GNN-LS method can be used to effectively identify and categorize a learner's preferred method of instruction. As a result, students will be better able to direct their own educations and progress through their courses. In addition, this method can aid in the development of further educational systems that can efficiently personalize learning on the basis of different models of learning styles.

V. CONCLUSION

This paper developed a GNN-LS approach for predicting learners' learning styles to improve the success of online learning. The proposed approach is helpful to provide resource recommendations since it predicts the learner's preferred learning style using a widely accepted FSLSM model. By modeling the observed learner's behavior as a bipartite graph, the proposed GNN-LS uses the graph representation learning technique to extract and encode the graph into a latent representation (encoded L-R sequence). These encoded sequences are mapped to four dimensions of FSLSM and the resulting features were used as input to the k-means clustering algorithm to group them into eight groups of FSLSM categories. The output of the k-means algorithm and the resulting features associated with each FSLSM dimension is further used for node classification using graph neural networks to predict the learner's preferred method of learning for the new or next sequence. Through experiments on the 2015 KDD Cup dataset, we discover that the proposed GNN-LS outperforms the state-of-the-art methods. The suggested GNN-LS has real-world relevance because it may be used with various e-learning systems and pedagogical frameworks. Future research will aim to refine the model so that it can effectively offer appropriate learning resource suggestions for various learner populations, taking into account their unique characteristics and learning styles.

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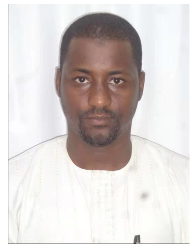

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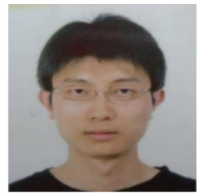

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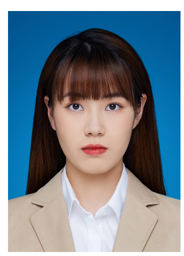

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