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ADAPTIVE AND DYNAMIC LEARNING STYLE CLASSIFICATION USING HYBRID LSTM-GNN FRAMEWORK AND SELF SUPERVISED LEARNING IN E-LEARNING

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ABSTRACT

Learning style identification is a crucial part of enhancing personalization in e-learning platforms. Due to dynamic and unstable user behavior, learning style detection needs more appropriate labeled datasets. The contribution of the work is developing a novel learning style classification model, "Dynamic Learning Style Classification (DLSC)", with a new learning style named as "Cumulative learning style model (CLSM)", which is based on implicit and explicit feedback, access log, and contents from a custom-built e-learning platform. The key process behind this model is collecting both implicit and explicit data from a dynamic e-learning platform and applying it to the DLSC to effectively find the learning style. The proposed learning style consists of 17 styles which are developed from the analysis of existing learning styles. A different set of attributes in the implicit, explicit category, Artificial Intelligence (AI)-driven, and behavioral tracking attributes are gathered and used to find the learner learning style. Learner's navigation patterns, time spending patterns, User Interface (UI) interactions, and more implicit attributes, such as learning goals, preferred content format and other preference based explicit attributes are gathered to make the learning style identification process much stronger. For effortless training and effective feature extractions, Graph Auto Encoder (GAE) with self-supervised learning (SSL) is proposed. Finally, the integration of Long short-term memory (LSTM) and Graph neural network (GNN) made to the better classification result. The experiment has been carried out and collected many raw data and then it is processed through a collective machine and deep learning algorithms. The results show the proposed model achieves a higher amount of precision and accuracy of **97.8 %** in dynamic learning style detection.

Keywords: *Learning Style Classification, Adaptive E-Learning, Graph Autoencoder (GAE), Self-Supervised Learning (SSL), Long Short-Term Memory (LSTM), Graph Neural Network (GNN).*

1. INTRODUCTION

The new trends and growth of digital education, e-learning plays a vital role in delivering the knowledge across various technology and domains. E-learning platform provides much flexibility and facilities to learn from their location, time and schedule. The popular e-learning platforms like moodle[1], skillsoft [2], Pluralsight [3] facilitates more options and insights towards completing a course with immersive knowledge. As the learner count increases, the need of personalization and attention process also increased [4]. This is crucial in terms of improving the learner learning performance, engagement and motivation. Traditional e-learning platforms often stick on static learner adaptation process and explicit data sources to identify learner's preferences. Sudden boom in the AI and Deep learning techniques gradually increases the ability to adopt these areas in e-learning in providing optimal personalized services. These techniques utilize massive amount of digital data's like user behavior logs, interaction with the pages, quizzes, courses and navigational patterns in the e-learning platform to predict the styles of the e-learner's. However, in the real-time, many existing systems utilize only a subset of information and lack in multimodal data collection across the platform. In the process of learning style identification, tasks like labeling data, optimal selection of learning styles among existing styles

[5], making adaptive to the dynamic platform data, selection of machine learning algorithms are the intricate and critical process. Some of the works end with the solutions overlooks complicated feature similarities among learners without latent representations from those attributes like content engagement, page navigation formats, quiz attempts and session patterns are ineffective.

To address these confines, we introduced a novel learning style classification model DLSC that integrates implicit and explicit learner attributes with the new learning style CLSM that built from the customized e-learning platform. This study is specifically scoped to the automated in dynamic manner according to learner activities within the e-learning platform. The proposed work uses a multimodal data collection approach, capturing various aspects of learner interaction from the custom-built e-learning platform. Meanwhile, the complex and hidden features are extracted with the integration of GAE and SSL. The utilization of GAE helps in representing learner relationships and behaviors in a graph-based structure, while SSL enhances the robustness of feature learning without requiring manual labeling. So, effort of self-labeling can be reduced in this process. Finally, for effortless classification of learning styles dynamically, the model leverages a hybrid architecture combining LSTM networks with GNNs. This combination allows the system to learn temporal patterns in learner behavior along with structural dependencies, enabling accurate and adaptive classification into 17 different learning styles. The primary research contribution of this paper is the proposal of the DLSC model. To the best of our knowledge, DLSC is a first LSTM-GNN hybrid architecture classify learners into 17 fine-grained learning styles using a custom learning style model (CLSM) built on multimodal implicit and explicit behavioral data. The proposed framework can assist e-learning platform designers and educators in automatically profiling learners and delivering personalized content recommendations, thereby reducing manual intervention and improving learner engagement and outcomes.

The key contributions of the proposed study include:

- A new design and implementation of a custom e-learning platform with novel custom learning style CLSM with 17 new learning styles.
- The use of GAE and SSL for effective feature extraction from raw learner logs and activities.
- Developed a novel DLSC model based on LSTM-GNN to dynamically classify learner learning style from the developed new learning styles.
- Developed a comprehensive dataset from implicit and explicit sources for accurate learner style identification.
- Performed a comprehensive analysis of existing learning styles and its results compared with the proposed CLSM.
- A detailed evaluation using synthetic learner data demonstrating improved adaptability and classification accuracy.

The remaining sections of the paper organized as follows. The detailed background study to understand the different learning styles, literature review of very recent studies and problems are discussed in section 2. The section 3 provides detailed about the proposed custom-built e-learning platform and learning styles with its attributes. The detailed research methodology of the proposed model is given in section4. Experimental results with data collection and setup are discussed in section 5. The final part of analysis and interpretation is discussed in section 6 and section 7 concludes the work and provides the continuity of the next phase as our future work.

1.1. Learning Styles

This section provides the existing learning styles to get the idea about the difference we made in CLSM. The most recent studies are discussed in this section to delve into the core idea. Personalized adaptive learning model utilizes several existing Learning Styles (LS), the most frequently investigated and utilized LS are discussed in this section. This analysis made the importance of developing new LS for dynamic learning style classification. Among various LS, VARK [6], Kolb's [7], FSLS [8], Honey & Mumford [9] and multiple intelligence by Gardner [10] are discussed in the Table 1 in appendix.

The study on these LS models shows, the importance of generating new LS model, which doesn't rely on static questionnaires, because the utilization of the existing LS in dynamic e-learning platform with adaptation and personalization doesn't give dynamic LS classification or even not apt for evolving learner behavior, especially in online platforms.

1.2 Recent Study

A Spectral Clustering and Quadratic SVM (E-SVM) model was proposed to classify e-learning styles based on web usage logs. The system extracts behavioral patterns from students' click streams, navigation history, and time spent on activities. The Spectral Clustering technique groups learners with similar interaction patterns, while Quadratic SVM (E-SVM) enhances classification accuracy. The study demonstrated 97% accuracy, 96% specificity, and 96.3% sensitivity, outperforming traditional models such as FSLSM and FCM. However, this approach relies heavily on structured web data and does not adapt to unstructured or evolving learner behavior, limiting its applicability in real-time adaptive learning environments [11]. A semi-supervised learning model was introduced to classify Felder-Silverman Learning Styles (FSLSM) in an online learning environment. The system employed SSL with limited labeled data to improve classification efficiency. The model leveraged quiz interactions, discussion forum participation, and study resource engagement as key features for determining learning styles. The experimental results showed that the system achieved 88.83% and 77.35% classification accuracy across two different courses. However, this approach is highly dependent on the availability of labeled data, making it challenging to scale for large e-learning platforms with evolving learner behaviors [12].

A hybrid deep learning model combining Latent Dirichlet Allocation (LDA) and neural networks was explored for FSLSM-based learning style classification. The LDA model was utilized to extract hidden patterns from textual learning interactions, while the deep learning model refined learning style predictions based on previous user engagement. The model effectively captured both explicit (questionnaire-based) and implicit (behavioral) learning patterns, leading to a classification accuracy of 95.54%. However, this system primarily relied on textual data and lacked real-time adaptability, making it less effective in handling multimodal learning environments with video-based and interactive content [13].

The authors in [14] developed a Bayesian network–driven classifier, employing Object-Oriented Bayesian Networks (OOBNs) to infer FSLSM learning styles. They trained this system on responses from the questionnaire model named as Index of Learning Styles (ILS), enabling it to assign learners to one of four dimensions such as Active_Reflective, Sensing–Intuitive, Sequential–Global, or Visual–Verbal. By modeling the probabilistic interdependencies among learner behaviors and preferences, the network achieved higher classification accuracy. However, because the design was inherently static and unable to adjust as learners' behaviors evolved it fell short of supporting truly adaptive learning management systems. A context-aware learning style recommender system was developed using K-Means Clustering for grouping and Decision Trees for classification tasks [15]. The system analyzed real-time learner interactions within an online platform and suggested personalized content based on their Felder-Silverman learning style [8]. The clustering technique grouped learners with similar behavioral and cognitive patterns, while Decision Trees further refined the classification to provide adaptive recommendations. The study reported an overall accuracy of 96% in identifying learning styles, showing promising results for personalized e-learning applications. However, the model faced scalability challenges and was unable to continuously learn from new interactions, making it less effective for long-term adaptive learning environments [15].The summary of the literature given in Table 2. Unlike prior works [11–15] that based on static models, labeled data, and limited single input data. But, the proposed DLSC framework is the first to integrate multimodal behavioral data and a novel 17-style CLSM within a dynamic e-learning platform.

1.3 Issue Addressed

However, the recent works and existing LS models have good impact on various directions; some of the real-time and research-oriented problems should be discussed. The present LS classification models often struggle with dynamic domain adaptation, multi modal learning issues, implicit data collection and usage and labeling the training samples. The traditional approaches like FSLSM and ILS rely on static questionnaires, failing to capture evolving learner behaviors. Recent machine learning oriented studies with the Spectral Clustering with Quadratic SVM and semi-supervised learning improve accuracy but depend on structured data and labeled datasets, limiting their feature sets. Some studies used Deep learning models like LDA-neural networks and Bayesian networks can elevate the classification but lack adaptability to dynamic learning patterns. Recent CNN-based sentiment analysis and bipartite graph

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embedding techniques offer more adaptability, however technique faced computational complexity issues. There is a need for a real-time, customizable, dynamic and adaptive learning style classification system that integrates deep learning, graph-based models, and self-learning mechanisms to improve adaptive dynamic personalized e-learning.

1.4 Problem Statement:

The current learning styles and personalization are not fully adopted for dynamic e-learning environment. The integration of Implicit and explicit data collections are not dynamically collected and used for the learning style classification. The existing learning style classification is lack due to the static questionnaires and pre-defined labeled datasets. This is inadequate for real-world e-learning environments. To address these issues in the current learning style classification models, the following research questions guide this work:

RQ1: How the combination of implicit and explicit learner behavioral data helps in improving learning style classification accuracy?

RQ2: Can the integration of GAE with SSL reduce manual labeling process dependency on training data while preserving feature quality?

RQ3: How much the hybrid LSTM-GNN architecture outperforms existing learning style classification models in dynamic learner style classification?

RQ4: Is the proposed work can effectively handle data imbalance?

RQ4: Can a custom learning style model (CLSM) with 17 fine-grained styles offer more exact learner profiling compared to conventional models such as FSLSM and ILS?

Based on these research questions, the proposed work aims to achieve optimal results in terms of accuracy and loss metrics.

2. MATERIAL AND METHODS

This section gives the details about the complete base development to achieve the LS classification model. The core intention of the work is to create a new learning style model which is suitable for the custom-built e-learning platform.

2.1 Proposed E-Learning Platform:

Rather than collecting datasets from other sources, the dynamic enriched web-based e-learning platform is created for an institution with many real-time features. This e-learning platform developed with the intention to support the dynamic, adaptive personalized e-learning with the implicit and explicit data collection. The proposed e-learning platform has numerous features specially developed for the computer science courses. The platform collects learner session logs, course material access log, learners learning activities like quizzes, content access and other logs and stored in real time database. These data are used dynamically for classification and learner's preferences can be identified.

2.2 Proposed Learning Styles:

We propose a new learning style, the CLSM, which is based on implicit and explicit feedback, access log, and contents from a custom-built e-learning platform. The classification of learners into 17 learning styles in this platform is created on a rich set of 25 multimodal attributes, grouped into explicit (user-provided) and implicit (system-tracked) types. These attributes classify learners into 17 distinct learning styles, and numerous implicit and explicit attributes are used, each representing unique behavioral patterns and content interaction preferences. The details about styles and their description are given in Table 3.

3. RESEARCH METHODOLOGY

In the proposal, the hybrid learning algorithms are used to create a robust and effective model for learning style classification, which utilize both machine and deep learning. This model can identify dynamic learner style from the interaction log which is collected within the e-learning environment. The proposed DLSC model stays on a structured, data-driven approach to classify learners. DLSC consist of four phase methodology, which includes a novel multi-modal data collection, hidden pattern detection, sequential behavior modeling, and learning style classification. To effectively extract a set of features from the user dynamic interaction logs, an effective e-learning platform is developed and utilized. The proposed work incorporated with a new learning style developed from the e-learning platform which consists of 17 learning styles from multiple features. Unlike existing learning styles, the proposed learning style model can specifically detect user styles rather than generalized class.

The proposed approach integrates e-learning platform with the multi model data collection framework to support dynamic data collection. The proposed work can update the learning style periodically when the learner data is updated over the e-learning platform. The proposal supports both supervised and un-supervised labeling process with the hybrid learning techniques. Existing learning style classification falls on the generic learning style categories, to overcome this issue, the proposed work diversified the styles into a more suitable form for modern learners. The overall flow of the methodology is depicted in Figure 1. That initializes the data collection using multi-modal framework, which has the ability to collect both implicit and explicit data from the e-learning platform and performs feature extraction with the integration of GAE and SSL, then the graph construction finds the behavioral similarities and then finally the fusion layer of LSTM-GNN gives the dynamic learning style class for the learner according to their past behavior and performance. The workflow of the proposed methodology is shown in Figure 1.

The proposed model relies on the multi-modal data collection, which includes explicit and implicit data collection, pre-processing the weblog files, and converting into the desired dataset format. The impact of GAE, which is class of neural network, gives the data relationship mapping process in unsupervised manner. The users are treated as nodes and the content are defined as edges; these relationship mapping avoid the need of labeling process. After the initial feature extraction from the GAE, the SSL applied to find the hidden features. This also performs the grouping process of learners to find the learning behavior similarity. Finally, the fusion of LSTM and GNN allows the system to classify the learner style into a specific class and avoids the diversify results. Applying this hybrid mechanism of machine and deep learning techniques are cost effective in data labeling and re-training processes and adaptive to the personalized e-learning in dynamic environments.

3.1 **Multi-Modal Data Collection** Framework (MMDC)

To collect the data from e-learning platform, the multi-modal data collection framework is introduced. To cover all the 17 style of learning, it involves the data collection process from explicit attributes like user preferences, goals and self-assessment information's. And the implicit attributes like clicks, session duration, navigation patterns, and quiz behaviors etc., MMDC also collects behavioral logs like material access patterns, time spent on each course and materials along with its type. And some interaction-based data from forums, discussions and feedback forms also collected. The MMDC enables the personalization based on diverse data types and it can update on live interactions. The accuracy of classification when there is insufficient explicit data might be low and affects the classification process. It overcomes the issues and enables classification into granular styles with better accuracy. While calculating personalized learning preference of every learner, the implicit data acts more important role. The navigation patterns identified to track the learners learning path. This process identifies whether the learner follow Sequential or non-linear navigation patterns.

From the illustration Figure 2, the user session logs are gathered and navigation pattern for user s1 is calculated as "non-linear", where the user jumps between topics in every attempt see figure.3.

3.2 Graph Auto Encoder (GAE):

After data collection from the MMDC step, feature extraction is performed to capture and analyze the complex interaction behavior of learners within the e-learning platform. For this process, we propose **GAE.** Here latent feature represents by constructing bipartite graph, and this captures the interaction dynamics between learners and learning resources. The collected explicit and implicit raw data are usually unstructured and high-dimensional, which make difficulty in direct analysis and classification. To support the dynamic classification, learner interactions and engagement patters are transformed into structured feature vectors. GAE performs such process with graph representation. It is considered as an essential part of DLSC for feature extraction and complex relationship capturing between learners and that finds the patterns, correlation and similarities between various learner e-learning activities. The GAE works by constructing the graph with edges and nodes. Each node in the graph represents a learner and the edges exist between learners based on the course material, similar learning paths, and other similarities in learning style. The feature matrix X, which is the multimodal attributes with both implicit and explicit learner and adjacency matrix A, which represents the learner-learner interaction graph are used as input in GAE. The learner embeddings are computed using the GCN using Eq (1).

$$Z=GCN(X,A) \quad (1)$$

This produces the value Z, which is a lower-dimensional relational and attribute context.

3.3 Self-Supervised Learning (SSL) For Refining Behavioral Embeddings:

In the proposed framework, after extracting initial node embeddings using the GAE, we apply SSL to improve the quality and structure of these latent representations. SSL does not need the labeled data, which is needed for the dynamic e-learning platform. The SSL learns meaningful patterns from unlabeled data by solving pretext tasks. These tasks do not require human-labeled output but are automatically created from the available data by its own. The notable point of using SSL here is to make sure that user representations (embeddings) capture similar learning behaviors even when users interact with different resources. For example, two users may never visit the same page but may exhibit similar learning patterns such as revisiting quizzes, watching videos multiple times, or scrolling slowly through textual content. SSL helps group such users together in the feature space by treating them as positive pairs based on their behavior graphs. To perform SSL, we adopt a contrastive learning approach. In this setup, we first apply graph augmentation techniques to generate two slightly different views of the same user interaction graph. These techniques include, Edge dropout, which always randomly removing a few user-resource interaction edges and Feature masking. The feature masking hides certain interaction attributes such as time spent and clicks frequency. The edge drops out and feature masking views are passed through the encoder, and the resulting embeddings are compared using a contrastive loss function. The model is trained to pull together embeddings of the same user from both views (positive pairs) and push back embeddings from different users (negative pairs). With this step, the hidden features are gathered. This method helps generate stronger and more consistent behavior-based representations. For example, learners who frequently interact with multimedia and spend extended time on quizzes are grouped with similar users, even if the exact pages they accessed are different. Once the SSL-refined embeddings are obtained, we perform clustering the data. We observe that the clusters become more well-defined, with similar learner types grouped together more effectively. This is achieved using a contrastive-style loss function as shown below:

$$LSSL=\|f(x)-f(x\sim)\|2 \quad (2)$$

Where, **x** represents the original learner-content interaction vector which is derived from session logs and quiz attempts. x~ is an augmented variant of x, produced through techniques such as masking, noise injection, or temporal shuffling, f(·) is the feature encoder (e.g., a GAE-based encoder), and ‖·‖2 denotes the squared L2 norm measuring the distance between two embeddings. The integration of GAE into the SSL encourages the model to learn optimal hidden features from the multi modal data and helps in better learning style identification. This process eliminates the need of labeling process and refines the raw dataset and makes it suitable for the classification process.

3.4 DLSC Using LSTM-GNN

The proposed work performs dynamic learning style classification where the learner's data are continuously evaluated from their learning objective, preferences, study and performance patterns. The existing classification system failed to recognize the transitions in different time sequence, to overcome this issue, the module LSTM-GNN is applied to handle both sequential and relational learning behaviors. We utilize the well-known time-series data model LSTM for sequential pattern identification in DLSC process. This can effectively find the learning style and their transition over time, so this is very adaptive for dynamic e-learning platform. In the experiment, a learner L1 is classified as visual learner initially, but after collected more session logs, the L1 may fall under a different class like "reading-writing". These time–dependent relationships and features provide dynamic learning style classification with the help of LSTM. The equation (3) represents the mathematical formulation of the LSTM hidden state update.

$$ht=f(Wh\cdot ht\text{-}1+Wx\cdot xt+b) \quad (3)$$

Where, ht is the current hidden state (representing the learner's updated style) which can be updated periodically or after hitting a session log count. The

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threshold can be dynamically adjusted in the model configuration. h^{t-1} is the previous learning state, xt is the current learner interaction, Wh,Wx are trainable weight matrices, bb is the bias term, and ff is an activation function. This formulation allows the DLSC model to maintain a memory of past learning behaviors while adapting to new learning patterns.

In the DLSC model, we combine time-based learner behavior with their relationships to others for better classification. First, each learner's activity sequence such as time spent, clicks, or quiz performance over several sessions is processed by an LSTM. The LSTM analyzes patterns over time and outputs a fixed-size vector called a hidden state ht. After calculating ht, graph construction is performed based on learner's behavior similarity. The input of GNN from LSTM is the hidden state ht, where the similarity between learners is treated as a new feature. This updated feature vector is passed through the softmax layer in the classification model.

3.5 Classification Process:

After successful implementation of the DLSC model, with the feature extraction and behavioral modeling, the final step is assigning learners to one of the 17 newly developed CLSM learning styles dynamically. Unlike conventional models that rely on limited classes where the generalization is the problem. The proposed CLSM allows learning styles to emerge dynamically based on actual behavioral data and it is wide and has more specific learning style, which can effectively identify the learning preferences and possible improvements based on the style. The DLSC model follows a structured classification pipeline, which highlighted in the following algorithm steps.

Algorithm 1: DLSC Model

Input: I: Learner interaction data from MMDC, U: Set of learners, C: Set of learning content

Output: Predicted learning style L∈{L1,L2,…,L17} for each learner

Step 1: Multimodal Data Collection: Collect explicit attributes(e.g., quiz scores, preferences) and implicit attributes (e.g., time spent, clickstream) for each learner from the MMDC.

Step 2: Graph Construction and Feature Encoding: Construct a Bipartite graph G(U,C,E)G(U, C, E) with Nodes: learners U and content C, Edges: interactions (e.g., time spent, quiz engagement) . Apply Graph Autoencoder (GAE) to learn feature embeddings shown in eq(4):

$$F=GAE(G) \qquad (4)$$

Step 3: Feature Fusion process, combine embeddings with temporal and sequential data: Apply Self-Supervised Learning (SSL) to refine unsupervised patterns. Feed sequences into LSTM to capture temporal behaviors. Integrate with Graph Neural Networks (GNNs) to model relational influences

$$H=GNN(LSTM(SSL(F))) \qquad (5)$$

Step 4: Style Classification: apply the high-dimensional features H to classify each learner into one of the 17 learning styles using a dense classifier:

$$L=\text{argmax}\ (\text{Softmax}(W\cdot H+b)) \qquad (6)$$

Step 5: Continuous Adaptation and Re-Evaluation: Monitor new learner data I form in real-time. Recompute L.

From the overall algorithm steps, the proposed work collects detailed explicit and implicit details of learner "A" and initially predicts the learning style. After the threshold t of temporal value, the learner's session logs are gathered with possible implicit attributes and re-classify the learner into another class. It reflects in the platform dashboard dynamically after every access pattern change. Finally, the proposed DLSC model on CLSM learning style redefines learning style classification by employing machine learning and deep learning techniques on custom-built e-learning platform. The detailed methodology of DLSC continuously adapts learner behavior and provides high accuracy and performance in adaptive personalized e-learning platform.

4. RESULTS AND DISCUSSION

This section presents the detailed experimental details of the work along with the dataset description, performance analysis.

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4.1 Experimental Setup

To review the efficacy of the DLSC model, trials were conducted on a custom-built e-learning platform developed with latest web technology. This platform was designed to simulate a realistic and interactive learning environment that supports the dynamic tracking of user behavior across multiple courses and content formats. The primary aim of this setup was to capture both implicit and explicit learner data in a natural and adaptive context. The dataset used in the experiments was collected from 200 learners enrolled in 10 different online courses, covering a range of topics such as Programming Fundamentals, Data Science, and Soft Skills. Each course provided diverse learning materials, including text-based content, videos, interactive quizzes, and assignments, which enabled the system to observe varied learning behaviors. Implicit data's like navigation paths, time spent on activities and interaction types were automatically logged, while explicit data was obtained through learner input like content preferences and defined learning goals. The deep learning modules for behavior analysis and classification including GAE and other neural components were implemented using Python, leveraging TensorFlow and PyTorch frameworks. These modules processed the collected multi-modal data to extract patterns and identify learning styles dynamically. All experiments were conducted on a system equipped with the advanced processer and configurations like, Intel Core i7 processor, 32GB RAM, and an NVIDIA RTX 3080 GPU, ensuring the efficient execution of model training and testing phases.

4.2 Data Collection

In the evaluation process, a synthetic yet realistic e-learning environment was developed and collected dynamic user interactions, behavior logs, and learning progress from the environment. The platform recorded both explicit and implicit learner attributes through user registration, session logs, quiz performance, course material interaction, forums, feedbacks and learning behaviors across the platform. Table 4 shows the dataset summary with different parameters.

Table 4. Dataset Summary

Parameter	Value
Total Learners	250
Number of Courses	10
Explicit Attributes	10
Implicit Attributes	15
Learning Styles Classified	17
Session Logs per Learner	20–50
Quiz Attempts Recorded	5,200
Course Materials Accessed	7,400

This dataset collected from the e-learning platform from 250 learners of the institute. The website created with 10 unique computer science courses with 25 attributes. The proposed 17 styles and the dynamic adaptive process are performed using the session xlogs of each user.

4.3 Experimental Results

The proposed architecture incorporates MMDC for data collection from the e-learning platform, GAE and SSL for feature extraction, followed by a hybrid LSTM-GNN model for classification. The experiment was conducted in Python 3.10 using TensorFlow and PyTorch frameworks, with a SQL Server backend for data storage.

4.4 Performance Evaluation

The proposed dynamic learning style classification proves its efficiency in different terms like accuracy, precision, recall and Receive Operating Characteristic curve (ROC). The average accuracy of the proposed model is 97.8%. The values are calculated from the 250 users during the three-month period. Finally the learner's records were categorized into 17 distinct learning styles using multi-class classification, where the existing system failed to perform more deep class detection, the proposed work has small number of dataset for training. The dynamic adaptive classification updates the results based on the updated user session logs and other interaction data. The proposed work performs the classification process in multi-layers, where the ablation study proves the performance of utilizing each model gives better results.

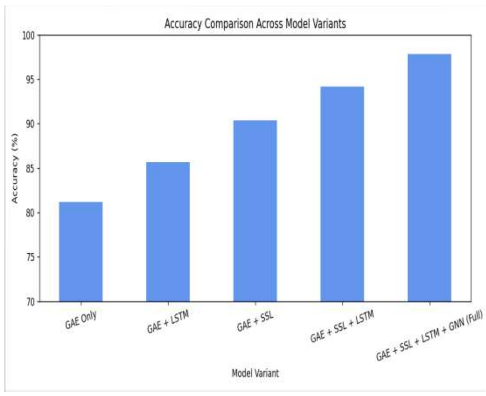

Figure 4: Ablation study graph of the DLSC model

The ablation study in figure 4 clearly demonstrates the impact of integrating multiple learning modules in the proposed DLSC framework. When we used only the GAE in the feature extraction process, the model attained 81.2% accuracy. Because, the initial feature extraction failed to cover all the styles. This shows it could grasp the structure of learner interactions, but the hidden behavior patterns are failed to detect. To overcome this issue, the additional module "SSL" is incorporated, and this can reduce the need of labeling process and increases the accuracy by extracting hidden attributes. After adding LSTM, the sequence of learner actions is gathered, and this increased accuracy to 85.7%. This boosted the accuracy to 90.4%. When both SSL and LSTM were used together, the accuracy increased further to 94.2%, showing how well the two methods work together. And this solves the RQ2. Finally, when we iteratively add each module like GAE, SSL, LSTM, and GNN, the model achieved its best performance of 97.8% accuracy.

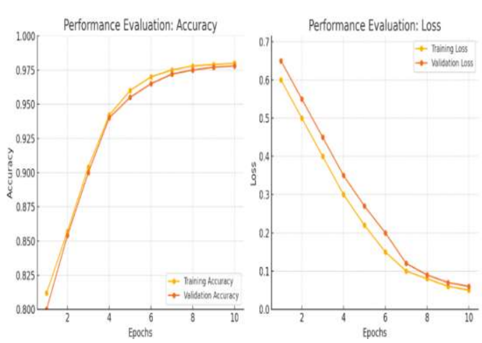

Figure 5.0 Accuracy and loss metrics Evaluation : (a) Training and validation accuracy; (b) training and validation loss

The accuracy plot in terms of training and validation shown on figure 5 (a) and the values shows that the model is performs better classification with highest accuracy, the figure shows the both training and validation accuracy increases from 78% to maximum of 98% in six epochs. The loss is plotted in figure 5(b) in terms of training and validation, which drop from approximately 0.45 and 0.48 down to 0.08 and 0.10. These curves together show that the model is better with every epoch and its shows it doesn't falling into over fitting.

4.5 Discussion And Comparisons

The Figure 6 presents a comparative analysis of various learning style classification techniques based on their accuracy. The combination of Spectral Clustering and Enhanced Support Vector Machine (E-SVM) achieved a high accuracy of 97%, demonstrating its effectiveness in grouping and classifying learners based on behavior patterns. SSL, although flexible and capable of learning from unlabeled data, yielded a lower accuracy of 88.83%, indicating possible limitations in capturing complex learning behaviors without explicit supervision. The method combining LDA with a neural network performed better, with 95.54% accuracy, by leveraging topic modeling and deep learning to fetch consequential attributes from learner activity data. The use of Convolutional Neural Networks (CNN) in conjunction with sentiment analysis reached 93.81% accuracy, showing the potential of analyzing emotional or opinion-based data, such as forum posts or feedback, for learning style identification. Graph Embedding paired with GNN attained an accuracy of 95.76%, effectively modeling relational learning behaviors within a graph structure. The highest accuracy was achieved by the proposed DLSC model, which integrates advanced components like GAE, LSTM networks, SSL reaching 97.8%. This indicates the superiority of the proposed model in dynamically adapting to learner behavior and improving classification performance in real-time learning environments.

These comparisons collectively demonstrate that methods relying solely on structured or labeled data, such as E-SVM and OOBN-based approaches, plateau in performance when faced with dynamic and multimodal learner interactions. In contrast, the proposed DLSC model addresses these shortcomings by combining graph-based relational learning, temporal modeling, and self-supervised feature extraction, which collectively contribute to its superior classification performance. The improvement of 0.8% over the next best method (E-SVM, 97%) may appear marginal numerically, but is significant in the context of 17-class classification across multimodal and imbalanced learner data, where even small gains reflect meaningful improvements in personalization accuracy.

4.6 Analysis and interpretation

The DLSC model is implemented on a multimodal learner dataset obtained from the experimental adaptive e-learning platform. The objective was to classify learners into 17 distinct learning styles using both implicit and explicit features. The system employs a hybrid learning architecture composed of GAE for feature embedding, SSL for unlabeled data utilization, and a sequential fusion of LSTM and GNN to model temporal and relational learning behavior. The experimental evaluation was done using 10-fold cross-validation to establish model robustness and generalizability. The model reached a classification accuracy of 97.8%, with average precision and F1-scores above 0.93 for all classes. From the confusion matrix analysis, the accuracy among diagonal elements was high; this indicates good prediction of individual learning styles. Among the 17 classes, styles with high interactivity and content engagement were the "Tech-Savvy Learners" and "Visual-Spatial Learners," which showed a high degree of confidence in classification. Furthermore, our approach effectively handled data imbalance, reduces the need of labeling process and sparsity through SSL, enabling the utilization of unlabeled interaction logs, which constituted a large portion of the dataset and RQ 4 has solved here. The results affirm that the proposed architecture not only outperforms baseline methods but also maintains classification reliability during learner behavioral transitions, which is critical in adaptive learning environments.

The proposed findings are directly addresses RQ1 and RQ3, which is identified in this study. The successful combination of multimodal implicit and explicit data (RQ1) is evidenced by the F1-scores exceeding 0.93 across all 17 classes, while the superiority of the LSTM-GNN hybrid over standalone methods (RQ3) is confirmed through the comparative analysis in Section 4.5. However, it is important to acknowledge that the current evaluation is based on synthetic learner data generated from the custom platform, and results may vary when applied to real-world large-scale e-learning environments with greater behavioral diversity. Additionally, the current model assumes a fixed set of 17 learning styles defined by CLSM, and its adaptability to entirely new or emerging learner behavioral patterns remains an open issue for future investigation.

5. CONCLUSION

This study presented a novel DLSC This study developed a novel DLSC framework. This can directly addresses the problem of dynamic learning style classification in e-learning from custom learning style framework with 17 learning styles. This combines GAE feature learning with semi-supervised learning algorithm for style classification. Unlike existing classification model which is based on static questionnaires, labels and learning styles, the proposed model is dynamic and shows high performance in covering a rich set of the user's behavioral and interaction traits from multi-modal data-generating precise styles of learner classification into pre-defined 17 categories. The model achieved a classification accuracy of 97.8% with F1-scores exceeding 0.93 across all classes, outperforming state-of-the-art methods including E-SVM, LDA-Neural Network, CNN-based, and GNN-based approaches.

The DLSC model enables continuous observations and reclassification through dynamical alteration regarding person instances as time progresses, so that the real-time dynamics in behavior are maintained without any static classification force. The four research questions pointed in this study have been addressed: multimodal data integration improved classification reliability (RQ1), GAE and SSL effectively reduced manual labeling dependency while preserving feature quality (RQ2), the LSTM-GNN hybrid outperformed standalone models in dynamic behavioral adaptation (RQ3), and the proposed work overcomes data imbalance problem (RQ4). This study has set a landmark to take a step further, redefining the potentials of the model to benefit individualized learning through providing timely insight to ride-side learners and educators on changes in their preferences and behaviors.

6. FUTURE WORK

Regarding future investigation, the model may consider expanding to support a larger range of real-world datasets, for instance, in the context of mobile learning and a platform with multilingual content. Moreover, reinforcement learning could be incorporated with the Proximal Policy Optimization (PPO) or attention mechanisms to enhance the adaptability and interpretability of the model. Also, the model could further support recommendation system associated with the e-learning platform features. Furthermore, future work will focus on verifying the CLSM and DLSC framework on large-scale real-world e-learning platforms with more features. And this also can extend to address the open issues of other streams of learning and emerging learner behavioral patterns not captured by the current 17-style model.

ABBREVIATIONS

Artificial Intelligence (AI), Convolutional Neural Networks (CNN), Cumulative Learning Style Model (CLSM), Dynamic Learning Style Classification (DLSC), Enhanced Support Vector Machine (E-SVM), Graph Autoencoder (GAE), Graph Neural Network (GNN), Graphics Processing Unit (GPU), Linear Discriminant Analysis (LDA), Long Short-Term Memory (LSTM), Multi-Modal Data Collection Framework (MMDC), Proximal Policy Optimization (PPO), Random Access Memory (RAM), Receiver Operating Characteristic (ROC), Self-Supervised Learning (SSL), User Interface (UI).

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AUTHOR CONTRIBUTIONS

All the authors participated in planning the study, designing the data collection tools, collecting and analyzing data for the study.

CONFLICTS OF INTEREST

The authors declare that there are no conflicts of interest related to this research work. No financial, personal, or professional relationships have influenced the findings, analysis, or conclusions presented in this study.

ETHICS APPROVAL

This study was conducted in accordance with the ethical guidelines and principles.

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Table 1: Existing learning style models

Ref .No	Model Name (Author, Year)	Description	Strategy	No. of LS	Pros	Cons
6	VARK Model (Fleming, 1987)[6]	Classifies learners as Reading/Writing, Visual, Auditory, or Kinesthetic [6].	Use of multimedia, recorded lectures, hands-on activities.	4	Simple and widely used; helps personalize content delivery.	Oversimplified; many learners fit multiple styles.
7	Kolb's Experiential Learning (Kolb, 1984) [7]	This style refers concrete experience, abstract conceptualization, reflective observation, and active experimentation.	Case studies, simulations, practical applications.	4	Well-suited for hands-on fields like business and medicine.	Requires experiential setups, which may not be feasible for all learners.
8	Felder-Silverman Learning Styles (1988) [8]	Identifies dimensions: sequential-global, active-reflective, visual-verbal, sensing-intuitive.	Interactive activities, real-world problem-solving, structured content.	8 (based on combinations)	Covers a broader range of cognitive processing styles.	Complex to implement in traditional classrooms.
9	Honey & Mumford Learning Styles (1986)[9]	Sorts learners as 4 groups such as activists, theorists, reflectors and pragmatists.	Group discussions, self-paced learning, problem-solving exercises.	4	Used in corporate training, professional development.	Not as commonly used in academic settings.
10	Multiple Intelligences Theory (Gardner, 1983) [10]	Defines eight intelligences categorized as logical, personal, mathematical, linguistic etc.	Personalized learning materials based on intelligence type.	8	Recognizes a variety of talents and cognitive strengths.	Difficult to measure and implement effectively in standard education.

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Table 2.0: Deep Learning and Machine Learning-Based Learning Style Classification Models

Ref	Description	Learning Style	Algorithm	Category	Disadvantages
11	Uses Spectral Clustering and Quadratic SVM (E-SVM) to classify e-learning styles based on web usage logs. Extracts clickstreams, navigation history, and time spent to predict learning styles.	Own Q-SVM Style	Spectral Clustering, Quadratic SVM (E-SVM)	Classification	Requires structured web data; lacks adaptability to evolving learner behaviors.
12	Introduces Self-Supervised Learning (SSL) to classify FSLSM learning styles. Uses limited labeled data and analyzes quiz interactions, forum participation, and study resource engagement.	Felder-Silverman (FSLSM)	Self-Supervised Learning (SSL), Classifiers	Classification	Dependent on labeled data; lacks real-time adaptation in large e-learning platforms.
13	Combines LDA and Deep Learning for FSLSM classification. Extracts textual learning patterns and refines learning style predictions using neural networks.	Felder-Silverman (FSLSM)	LDA, Deep Learning	Classification & Sentiment Analysis	Limited to textual data; lacks real-time adaptability for multimodal learning.
14	Uses Object-Oriented Bayesian Networks (OOBN) to classify learners into FSLSM dimensions. Trained on the Index of Learning Styles (ILS) questionnaire.	Felder-Silverman (FSLSM)	Object-Oriented Bayesian Network (OOBN)	Classification	Static classification; does not adapt to changing learner behaviors.
15	Uses K-Means Clustering and Decision Trees to analyze real-time learner interactions and provide personalized content recommendations based on FSLSM.	Felder-Silverman (FSLSM)	K-Means Clustering, Decision Trees	Classification & Recommendation	Scalability challenges; does not continuously learn from new interactions.
Proposed	Custom e-learning platform with automatic learning style classification from a novel learning style model with 17 learning styles.	Custom CLSM (17 styles)	GAE, SSL, LSTM-GNN Hybrid	Classification & Adaptive Personalization	Currently classification is done. Recommendation based on the classification remains as future work.

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Table 3: Learning Style Categories (17 Types)

S.No.	Learning Style	Description / Key Features
1	Quick Learners	Low time per lesson, fewer quiz attempts
2	Slow Learners	High rewatch count, extended time on lessons
3	Visual / Visual-Spatial Learners	Interaction with infographics, videos, 3D/graphical content
4	Solitary / Self-Paced Learners	Self-assessments, customized pacing, minimal collaboration
5	Social / Collaborative Learners	Active in forums, group discussions, peer reviews
6	Gamified Learners	Engagement with leaderboards, badges, and gamified elements
7	Reflective / Introspective Learners	Frequent use of review logs, reflective journaling, pause/replay patterns
8	Goal-Oriented / Certification-Driven	High certification pursuit, goal tracking, structured paths
9	Immersive Learners	Usage of interactive /multimedia content, simulations, immersive modules
10	Adaptive Learners	Frequently adjusts learning paths, accepts dynamic quiz difficulty levels
11	Logical Learners	Prefers structured, reasoning-heavy content like logic puzzles, diagrams
12	Verbal Learners	Engagement with transcripts, podcasts, and spoken content
13	Tech-Savvy Learners	Uses multiple device types, interacts with advanced tools (e.g., coding IDEs)
14	Multitaskers	Simultaneous sessions/tabs, frequent context switching or pausing
15	AI-Driven Learners	Engages with AI recommendations, smart quizzes, content suggestions
16	Context-Aware Learners	Learning behavior changes with device, time, or location
17	Reading / Writing Learners	Heavy interaction with textual material, notes, articles, documents

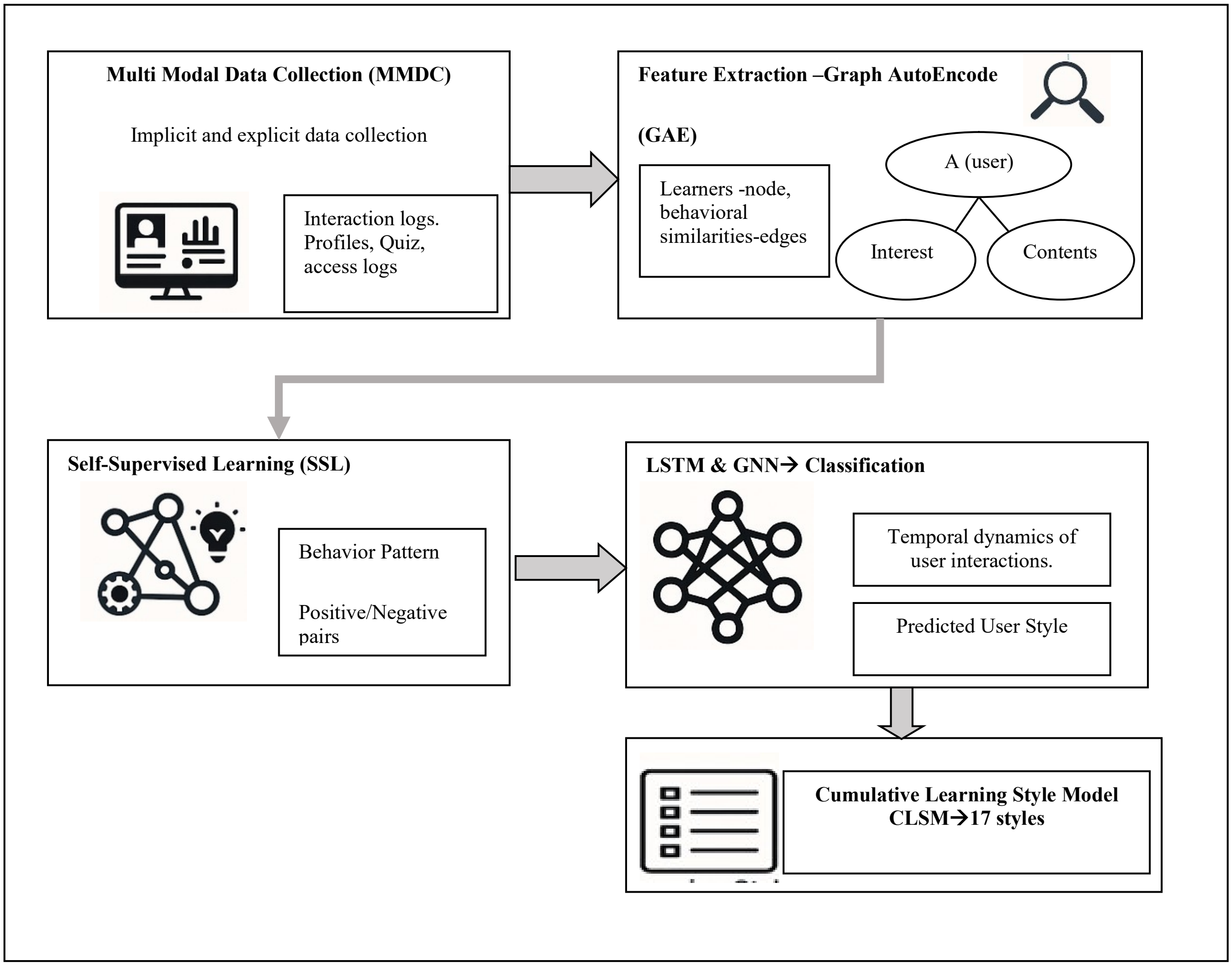

Figure 1: Proposed Methodology workflow

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Dataset Preview

Total_Time_Min	Avg_Session_Duratio	Session_Count	Video_Completion_R	Video_Rewatch_Ratio	Reading_Time	Quiz_Attempts	Avg_Quiz_Score	Forum_Posts	Peer_Interaction	Mobile_Usage	Laptop_Usage	Device_Switch_(
132.0	70.0	8.0	0.6406858964873114	0.414002934492399944	30.0	1.0	91.39223342487561	14.0	8.0	0.0	0.0	0.0
465.0	48.0	1.0	0.2695894079291281	0.12056021319543388	167.0	1.0	82.07019169541559	7.0	6.0	1.0	1.0	3.0
300.0	10.0	7.0	0.526762570456559	0.32149661068384877	278.0	1.0	83.62340569692341	11.0	1.0	1.0	0.0	1.0
136.0	12.0	1.0	0.4981508136098512	0.05800586978803176	171.0	2.0	73.72436766415427	17.0	7.0	1.0	0.0	2.0
101.0	86.0	13.0	0.407803027008261	0.27022256175491105	269.0	2.0	96.82544002651115	14.0	6.0	1.0	0.0	1.0
50.0	71.0	14.0	0.778736090950868	0.4536979973371476	111.0	4.0	69.77552517294168	16.0	7.0	0.0	1.0	4.0
151.0	72.0	7.0	0.5967005880630167	0.20854291454338925	232.0	4.0	62.831062592193675	13.0	2.0	0.0	0.0	0.0
496.0	34.0	3.0	0.2648369727261184	0.3989470346923308	68.0	4.0	49.78212021589546	13.0	6.0	1.0	0.0	3.0
244.0	65.0	11.0	0.3761465615598491	0.4772699764738375	256.0	2.0	87.17233913566348	17.0	9.0	1.0	0.0	4.0
360.0	42.0	8.0	0.7466070109276768	0.5563066916876716	137.0	2.0	84.06663592453549	19.0	8.0	1.0	1.0	4.0
488.0	47.0	3.0	0.26090468759224017	0.14078524911327212	292.0	4.0	63.06130231144809	17.0	2.0	1.0	0.0	4.0
117.0	15.0	14.0	0.880965531239015	0.23958954948558486	34.0	4.0	41.51160483755376	15.0	9.0	0.0	1.0	0.0
402.0	67.0	14.0	0.5961172216111794	0.09144960799825046	140.0	5.0	90.33983966308065	0.0	5.0	1.0	0.0	2.0
129.0	53.0	13.0	0.5844692618613184	0.5954901012950251	205.0	4.0	40.68507900724442	10.0	1.0	1.0	1.0	0.0
160.0	54.0	1.0	0.6739262277276141	0.5562005807545771	290.0	5.0	82.22198677774306	14.0	1.0	1.0	0.0	2.0

Figure 2: User session log data

UserID	NavigationType	NavigationPath
jeni128	Non-linear	loginpage -> Sessioninterest -> Course -> viewcourses -> Course_material -> Course_material -> coursematerials -> Course -> viewcourses -> quizpage -> quizpage -> qu
kk123	Non-linear	loginpage -> Sessioninterest -> Course -> viewcourses -> Course_material -> coursematerials -> Course_material -> coursematerials -> quizpage -> quizpage -> courseen
niralya	Non-linear	loginpage -> Sessioninterest -> Course -> viewcourses -> Course_material -> Course_material -> coursematerials -> Course -> viewcourses -> quizpage -> quizpage -> qu
nithya	Non-linear	loginpage -> Sessioninterest -> Profile_setup -> profile_setup_user -> Profile_setup -> profile_setup_user -> Profile_setup -> profile_setup_user -> Profile_setup -> profile_s
s1	Non-linear	loginpage -> /Elearning/Sessioninterest.aspx -> Course -> Course -> /Elearning/viewcourses.aspx -> /Elearning/courseenroll.aspx -> /Elearning/course_enroll.aspx -> logi
tamil1	Non-linear	loginpage -> Sessioninterest -> Course -> viewcourses -> Course_material -> Course_material -> coursematerials -> Course_material -> Course_material -> coursematerial

Figure 3: Navigation type from navigation path for user

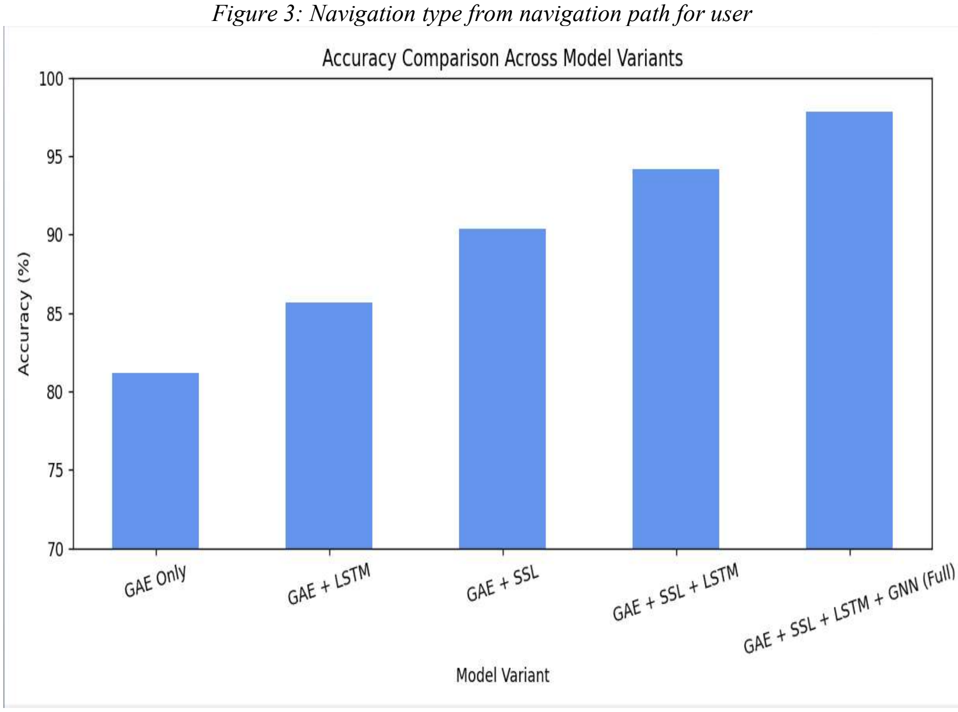

Figure 4: Ablation study graph of the DLSC model

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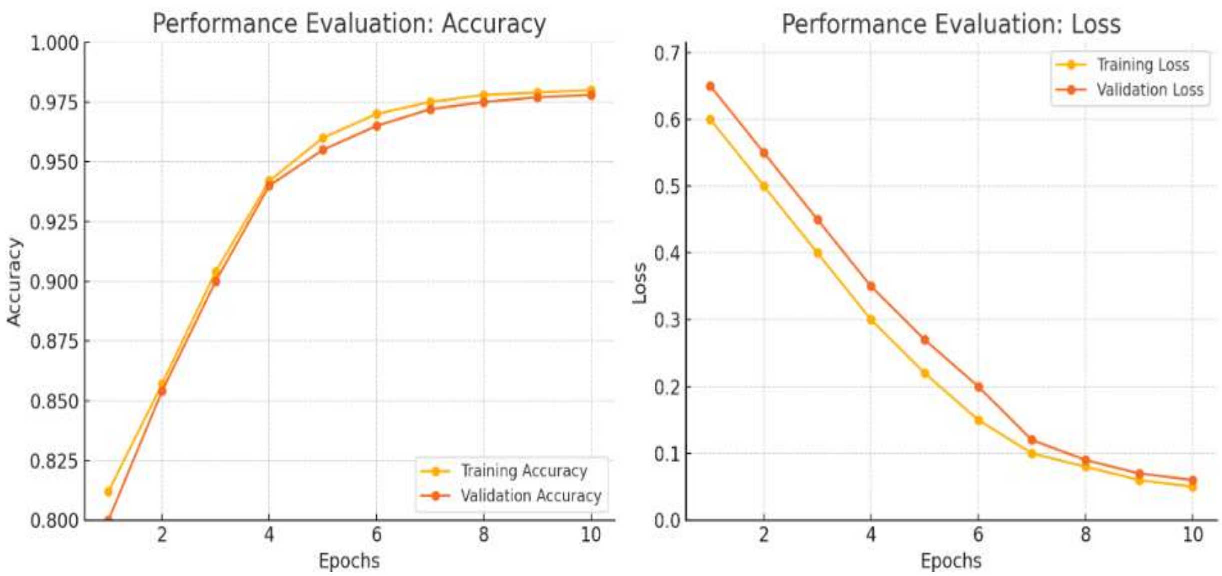

Figure 5.0 Accuracy and loss metrics Evaluation: (a) Training and validation accuracy; (b) training and validation loss

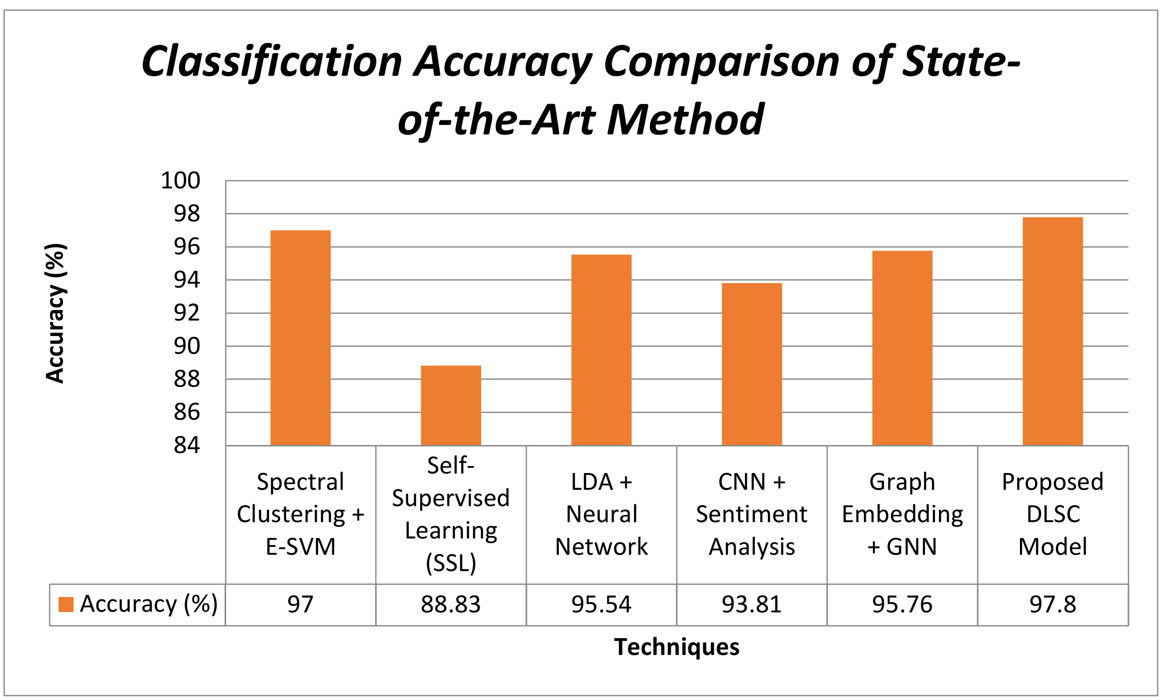

Figure 6: Classification Accuracy Comparison of State-of-the-Art Methods against the Proposed DLSC Model for Learning Style Classification