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Real Time Digital Twin Framework for Big Data-Driven Online Education Ecosystem

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Abstract

INTRODUCTION: The rapid expansion of online education platforms has created unprecedented opportunities for personalized learning but also presents challenges in monitoring student engagement, learning outcomes, and instructional quality in real-time.
OBJECTIVES: This research proposes a real-time digital twin framework for a big data-driven online education ecosystem, designed to continuously capture and analyze large-scale educational data that enhances learning and teaching effectiveness.
METHODS: The digital twin online learning dataset with 345 students is obtained. The obtained data are preprocessed by the data cleaning for removing duplicate entries and z-score normalization to normalize the numerical features in the dataset. By integrating big data analytics and Deep Learning (DL) techniques based on an Adaptive Monarch Butterfly Optimized Graph convolutional with Long Short-Term Memory (AMB-GC-LSTM) that combines Long Short-Term Memory (LSTM) networks for sequential student behavior prediction and Graph Convolutional Networks (GCNs) for modeling collaborative learning relationships, the system enables accurate prediction of student engagement, performance trends, and early identification of at-risk learners.
RESULTS: The AMB is employed to optimize the GC-LSTM parameters for higher accuracy and cost computation reduction. Experimental evaluation demonstrates that the digital twin-driven ecosystem improves engagement, learning outcomes, and teaching efficiency.
CONCLUSION: Comparison results provide an enhanced accuracy (0.965), precision (0.945), recall (0.974), and F1-score (0.959) with the Python implementation. This research presents a novel approach for integrating digital twin technology, big data analytics, and deep learning to create an intelligent, responsive, and scalable online education ecosystem capable of supporting continuous improvement in teaching and learning.

Keywords: Digital Twin, Online Education, Big Data Analytics, Real-Time Monitoring, Student Behavior Prediction, Personalized Learning

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1. Introduction

A supportive, evolving, equitable, and resilient platform that incorporates educational features, interconnections, and consequences is known as an effective education system. Using technological innovations to increase awareness, interconnectedness, and perception is the essence of effective education [1]. Instructors, pupils, and administrators are all receiving the ability to develop and employ efficient educational resources due to the substantial development and usage of technological advances in educational institutions [2]. A wide range of fundamental entrepreneurial abilities is identified with creativity and innovative education, which allows for developing highly talented individuals with leading personalities and creates an educational environment based on comprehension, creativity, and potential [3]. The widespread and expanding utilization of electronic devices as standard resources for work in learning institutions, along with the development of an innovative educational setting with online platforms as a major component, are the indications of the online platform development [4]. A global epidemic brings the significance of digital technologies and competency, along with the quality of online and hybrid education, to the core of learning improvements [5]. A popular way to characterize educational environment as a collection of ecosystems is provided by possessing distinct contributors, functional procedures, and interactions [6]. A rapid modification of instructional methods and student engagement emerged from the inclusion of technological advances into teaching concepts, which has completely transformed the learning ecosystem [7]. An alternative demanding of students is adopting technologies that depend on a deeper comprehension of online ecosystems to better serve the needs of every student [8-9]. Through increasing dependency on technology in education, technological advances are particularly essential to identify and investigate initiatives in the online education ecosystems [10]. Ecosystem availability, productive techniques, exploitation, and the difficulty of integrating numerous, separate entities with shared objectives are significant issues that highlight the vital significance of ecosystem regulation [11-12]. Data plays a crucial role in enhancing educational outcomes by enabling timely decision-making and personalized student support. For instance, continuous monitoring of student engagement and performance allows instructors to identify learning difficulties early and provide immediate interventions. This improves learning effectiveness and helps in reducing student dropout rates.

Developing a real-time digital twin method for a big data-based online education ecosystem that dynamically reflects the students, teachers, and learning materials is the major concern of the investigation. An Adaptive Monarch Butterfly Optimized Graph Convolutional with Long Short-Term Memory (AMB-GC-LSTM) method and big data analytics is developed for forecasting student engagement, improving personalization, detecting at-risk learners, and enhancing the effectiveness of education. In the proposed framework, big data provides large-scale real-time educational data, deep learning techniques analyze complex patterns and predict student behavior, while the digital twin enables dynamic representation and continuous monitoring of the learning environment. Together, these technologies work in an integrated manner to support intelligent, real-time decision-making and personalized learning.

1.1 Contributions of this Research

- To improve learning and teaching efficacy, this research suggests a real-time digital twin system for a big data-based online education ecosystem that continuously processes and analyzes enormous quantities of educational data.
- The research obtained a digital twin online learning dataset, and the obtained data are preprocessed by employing the data cleaning and z-score normalization methods to clean and normalize the data.
- An efficient AMB-GC-LSTM method is proposed for a real-time digital twin with a big data-based online educational environment.
- The proposed AMB-GC-LSTM method is evaluated by comparing the traditional techniques and shows improved results in predicting the student behavior in the online institutional ecosystem.

Through the advantageous utilization in corporate training, healthcare education, skill development platforms, and intelligent learning management systems, the proposed AMB-GC-LSTM technique facilitates immediate monitoring, customized recommendations, and early interventions.

Paper Structure: Section 1 provides a detailed introduction to the online education ecosystem. The relevant research is presented in Section 2. In Section 3, the research methodology was examined. Performance evaluations are demonstrated in Section 4. Discussions with limitations and future directions are determined in Section 5. Conclusions are explored in Section 6.

2. Relevant Research

A creative technology involving blockchain, Artificial Intelligence (AI), and 3-dimensional (3D) digital technologies appeared as a possible way to build an ecosystem for entrepreneurship education [13]. The findings showed that an ecosystem for entrepreneurial education had been developed effectively with improved simulation environments, communication facilitation, and production of useful information. It has information technology resource limitations and a lack of entrepreneurship experience. A virtual educational system that used facial expression detection technology to monitor students' progress in the classroom was introduced [14]. It provided instructors with beneficial knowledge to improve student outcomes and instructional methods. There was no information about the methods to improve the face expression detection algorithms by considering various educational circumstances.

Developing a DL-based evaluation system for online judicial education that allowed a thorough evaluation of students' learning outcomes, interactive communication, and learning patterns was explored in the research [15]. The model suggested in the research performed more efficiently at the levels of reliability, F1-score, accuracy, and recall while forecasting student performance, as demonstrated by the experimental findings. It limited the applicability of the model. To identify the substantial revenue losses in English online educational applications, the research [16] recommended a Multi-Scale Convolutional Neural Network based on Multi-Head Attention and the Hierarchical Long Short-Term Memory Network (MCNN-MHA-HLSTM) mechanism. Findings of the experiment showed that the suggested technique greatly enhanced the English online learning platforms' intrusion detection capabilities. Limited analysis of various datasets and actual online learning circumstances was observed.

An interactive teaching approach was investigated in the research [17]. It involved students communicating and interacting with the instructors and classmates to gain knowledge more efficiently. According to the research, providing the three basic psychological requirements of college students contributed to DL through increasing self-motivation, while interactive instruction significantly and directly facilitated the DL method. The research respondents' selection exhibited insufficient representation. A Hybrid Deep Learning (HDL) method using the enhanced convolution neural networks-based classification methods to forecast students' performance was suggested [18]. The hybrid methods showed higher prediction accuracy, indicating the model's superiority. Its absence of more recent developments in time-dependent data prediction was one of the drawbacks.

Innovative DL-based algorithms that continually record a student's emotions were presented in the research [19]. Based on the evaluation, DL approaches enhanced the learning outcomes and student engagement in online instructional environments. It limited the model's applicability to various student demographics in actual online learning environments. A unique method that utilized the Felder–Silverman Learning Style Model (FSLSM) to automatically detect the learning patterns [20]. The experimental findings showed that the provided method was significant in accurately identifying patterns of learning. There was a lack of enhanced understanding in influencing online education.

A Deep Neural Network (DNN) for student performance forecasting and students' partial pattern of educational activities was presented as an objective of the research [21]. The experimental findings demonstrated that a classification with an accuracy value of 0.5 and 0.84 has been attained by an online engagement pattern. It lacked the DNN's hyperparameter and training parameter selection mechanism. The Recurrent Neural Network (RNN) technique for automatic text generation was effectively used to support a large online learning environment, as discussed in [22]. The findings demonstrated that the language model was capable of producing immediate human-written responses in a unique way to the information and circumstances to deliver the relevant assistance. A more comprehensive context, such as active conversations, predicted a divergent evaluation outcome with the limitations of the research.

The strong data processing abilities of the DL method were introduced for an adaptive educational evaluation platform [23]. The Offsets Minimum Sums (OMS) was utilized as the front-end processor. When compared to other parameters, OMS with DNN factors include 23 and 57, which safeguard almost 59.64% of the network factors. It was unable to adequately demonstrate the model's versatility. The online education system for the recognition of student's faces to track development in the classroom was suggested [24]. The accuracy of the suggested method was 87.62%. In numerous instances, learners' faces and expressions were not correctly identified when collecting the virtual classroom images.

The student's adjacent engagements with the conversation-based data were obtained from Massive Open Online Courses (MOOCs) in the research [25]. Examining the rate of dropouts or online learning behaviors, results have been made easier by the predictive outcomes. The research was unable to develop significant algorithms to enhance prediction performance. The primary concern of showing the emotional influence of teaching methods and student learning to identify students' emotions, the investigation [26] presented a DL technique. The outcomes of the experiment were positive, while the outcomes revealed issues with over-fitting.

The DL technique in an online English learning platform, while employing association rules and a clustering method to assess learners and learning materials, was suggested [27]. The instructor's parameter values and the online learner parameters were adaptively updated based on the online learner modeling determined by the research outcomes. Reduced improvement was shown in the sense of effectiveness and satisfaction with individualized learning resource recommendations. The revolutionary DL-based networked systems of communication for collaborative online learning platforms that include human-computer interaction for consideration were suggested in the research [28]. The suggested approach demonstrated improved precision and effectiveness. The systematic implementation of hardware was not focused on the research.

Establishing a predictive method for determining pupils at risk of dropping out before graduation was the main objective of the research [29]. Logistic Regression (LR) was created by including a regularization element. The suggested models attained an accuracy of around 84%, as indicated by the results. It failed to create a deeper model that evaluates the students' behavior in teachers' training evaluation. A recommendation algorithm for online learning materials based on DL was presented as a main concern of the investigation [30]. The model's superior real-time performance and high detection accuracy were demonstrated through testing a range of instructional resources. Constrained with a generalization to a variety of student demographics and learning systems. Gudivaka utilize AI and big data analytics to enhance personalized learning and student engagement in educational environments. This concept is extended in the proposed framework by integrating real-time digital twin and GC-LSTM models to enable continuous monitoring and accurate prediction of student behavior [31].

2.1 Research Gaps

There are significant limitations that were explored by the existing DL based online learning systems, including facial expression detection in online classrooms, which have difficulties with a variety of educational conditions [14]. The DL based evaluation system for online judicial education [15] had limited applicability across diverse learning ecosystems. Multi-scale attention-based models for English learning platforms [16] were constrained by inadequate analysis of various datasets. Modern developments in time-dependent data prediction were not evaluated by the HDL and improved convolutional methods [18]. There was no hyperparameter or training parameter selection process in the DNN's early performance prediction [21]. The proposed AMB-GC-LSTM, real-time digital twin method addresses the existing limitations by integrating big data analytics that captures the various student behaviors, collaborative interactions, and learning patterns. The proposed method supports sequential and continuous forecasting, which dynamically adjusts with real-time data and optimizes the parameters for accuracy. It allows individualized learning, and early detection of at-risk. The study presents an intelligent edge caching and computing approach to improve scalability and efficient data processing, supporting real-time data handling and faster prediction in the proposed framework [32].

3. Research Methodology

The research intends to develop a real-time digital twin method for a big data-based online education ecosystem that improves the learning and teaching efficacy. The digital twin online learning dataset is obtained from Kaggle. The obtained data are preprocessed by the z-score normalization and data cleaning that clean and normalize the information. The research allows for reliable prediction of student engagement, performance trends, and early identification of at-risk learners by combining big data analytics and DL techniques based on the AMB-GC-LSTM for continuous student behavior and collaborative learning relationships predictions. Figure 1 depicts the methodology process involved in the research.

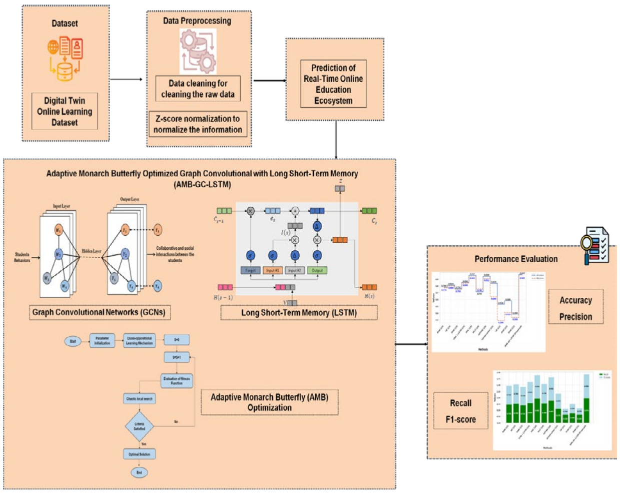

Figure 1. Flow of Research Methodology

The proposed real-time digital twin framework consists of multiple interconnected components, including data acquisition, preprocessing, model processing, and decision support. Initially, real-time student interaction and performance data are collected from the online learning platform. These data are then preprocessed using data cleaning and normalization techniques to ensure consistency.

The processed data are fed into the GC-LSTM model, where the GCN captures collaborative relationships among students, and the LSTM models temporal behavioral patterns. The optimized model continuously updates the digital twin representation of each student, reflecting their current learning state. Based on the predictions, the system generates actionable insights such as engagement monitoring and at-risk alerts, which support real-time decision-making for educators and system administrators.

3.1 Dataset

The Digital Twin Online Learning Dataset is obtained from Kaggle (https://www.kaggle.com/datasets/programmer3/digital-twin-online-learning-dataset/data). It contains real-time, big data-based logs of academic, behavioral, and engagement activities from 345 students in an online learning platform. Table 1 provides certain features presented in the dataset.

Table 1. Detailed Dataset Features

Features	Details
Student identifications and demographics	Student ID (a unique classifier for each learner)
	Age, gender, program_level
	Enrollment_status (active/inactive)
	Session_duration_min

Real-time engagement matrices	Clicks_per_session
	Pages_viewed
	Forum_interactions
	Video_watch_time
	Attendance_rate
	Engagement_score (0-100)
Behavioral and sequential activity features	Designed for LSTM input
	Daily_login_count
	Assignment_submission_timeliness
	Consecutive_missed_sessions
	Navigation_pattern_score
	Learning_streak_days
Collaborative learning features	Designed for GCN input
	Peer_interaction_count
	Group_activity_participation
	Network_centrality_score (In learning network)
	Collaboration_score
Performance indicators	Quiz_average_score
	Assignment_average_score
	Exam_score
	Final_performance_score (Target variable)
At-risk classification targets	At_risk (0-no, 1-yes) is used for predictive modeling and an early alert system.

The different feature categories in the dataset play a significant role in improving model performance. Student demographic information provides baseline context for understanding learner diversity and behavior patterns. Engagement-related features, such as session duration, clicks, and interaction frequency, capture real-time learning activity and are critical for identifying participation levels. Performance indicators, including quiz and exam scores, serve as key predictors for academic success. Additionally, collaborative features are effectively utilized by the GCN to model peer interactions, while sequential behavioral data are processed by the LSTM to capture temporal learning patterns. This combination of heterogeneous data enables more accurate prediction of student performance and risk levels.

3.2 Data Preprocessing

The process of cleaning, and eliminating the duplicates and unnecessary or irrelevant information from the obtained raw data is known as data preprocessing. This research employs the data cleaning and z-score normalization methods for normalizing and cleaning the information.

- **Data Cleaning:** It is one of the processes involved in data preprocessing. Components of the data that are deficient, inaccurate, incomplete, or inappropriate are identified during the data cleaning process. These forms of unclean data are replaced, altered, or deleted using data cleaning techniques. There are numerous ways to perform data cleaning that include correcting missing values, eliminating rows with duplicate values, and dropping redundant columns in the dataset.
- **Z-score Normalization:** It uses the data's mean (μ) and standard deviation (σ). If the true maximum and minimum amounts of information are unknown, it appears to be effective. The following equation (1) is applied to calculate the z-score normalization.

$$z - score = \frac{A-\mu}{\sigma} \tag{1}$$

Where the normalization value is indicated by $z - score$, and A indicates the initial value.Z-score normalization is selected due to its ability to standardize features based on mean and standard deviation, making it suitable for models sensitive to feature scale such as deep learning methods. Compared to Min-Max normalization, which is highly affected by outliers, Z-score normalization provides better stability when handling behavioral data with varying distributions. Although some engagement-related features may exhibit skewness, Z-score normalization helps in centering the data and reducing the impact of extreme values. This ensures more consistent learning and convergence of the GC-LSTM model.

3.3 Accurate Prediction Real-Time Online Education Ecosystem using an Adaptive Monarch Butterfly Optimized Graph Convolutional with Long Short-Term Memory (AMB-GC-LSTM)

A digital twin method for a big data-based online educational ecosystem is designed called AMB-GC-LSTM, that incorporates GCN with LSTM to continuously obtain and evaluate the large-scale educational data that improve the learning and teaching efficiency and the AMB optimization is used to optimize the hyper parameter in the GC-LSTM method while reducing the computational cost efficiency. The digital twin framework interacts with multiple data sources, including student activity logs, engagement metrics, performance records, and collaborative interaction data collected from the online learning platform. These heterogeneous data streams are continuously integrated and processed to maintain an up-to-date representation of each student within the digital twin.

The system follows a continuous update mechanism, where newly incoming data are periodically incorporated into the model through incremental updates. This enables the GC-LSTM model to adapt to recent behavioral changes and maintain prediction accuracy over time. By continuously synchronizing data and updating model parameters, the digital twin remains dynamic and responsive, supporting real-time monitoring and adaptive decision-making.

In the proposed digital twin framework, the system continuously updates its current state by synchronizing with incoming student interaction and performance data streams. The digital twin reflects the latest learning conditions of each student, including engagement levels and behavioral patterns. To manage potential delays in data acquisition, a buffered update mechanism is employed, where data are processed in short time intervals to ensure stability and consistency. Furthermore, the model is periodically refreshed using newly collected data, enabling adaptive learning and maintaining prediction accuracy over time. This ensures that the system remains responsive and capable of supporting real-time decision-making in dynamic educational environments. The comprehensive explanation of the proposed AMB-GC-LSTM method is as follows.

3.3.1 Graph Convolutional with Long Short-Term Memory (GC-LSTM)

GCN: It is a significant neural network, which adds the convolutional operation to graph structures. It is employed for modeling collaborative learning relationships so that the system enables accurate prediction of student engagement, performance trends, and early identification of at-risk students. The integration of GCN and LSTM enables complementary learning of both relational and temporal features. The GCN captures collaborative interactions among students, such as peer influence and group learning patterns, by modelling the relationships within the learning network. In contrast, the LSTM processes sequential behavioural data, capturing temporal dynamics such as changes in engagement and learning progression over time. By combining these two models, the framework effectively learns both "who interacts with whom" (GCN) and "how behaviour evolves over time" (LSTM), resulting in a more comprehensive and accurate prediction of student performance and risk. It separates the spatial dimension and the spectral domain depending on the various methods utilized to extract features. It is used to capture and extract the collaborative and social interactions between the students and teachers.

The selection of the GC-LSTM framework is theoretically motivated by the complementary strengths of GCN and LSTM in modeling complex educational data. GCN is well-suited for capturing relational dependencies by representing students as nodes and their interactions as graph structures, enabling effective learning of collaborative and social influence patterns. On the other hand, LSTM is designed to model sequential and temporal dependencies, making it suitable for analyzing time-evolving student behaviors such as engagement trends and learning progression. By integrating GCN with LSTM, the model simultaneously captures both spatial relationships and temporal dynamics present in online learning environments. This combined representation provides a more comprehensive understanding of student behavior, leading to improved prediction of engagement levels and early identification of at-risk learners compared to using either model independently.

A layer of security is used to describe the GCN, which is considered to eliminate interference using the filter to produce the classification outcomes of the input signal (W). GCNs are derived from graph signal processing and provide output (Y). Figure 2 illustrates the GCN architecture.

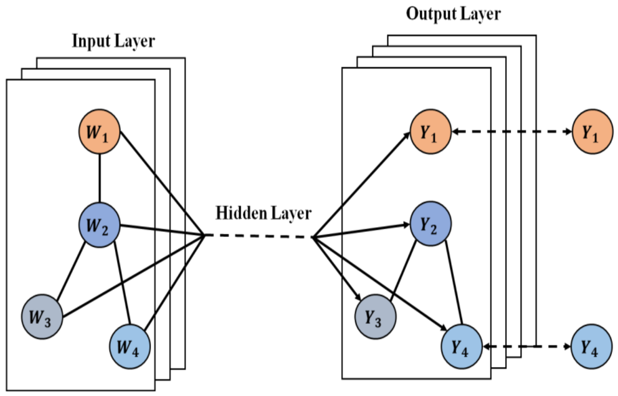

Figure 2. Architecture of GCN Method

The following is the expression for the spectral domain GCN, which is defined as the average of the signal and the filtering function (Equation 2).

$$G_\theta * a = \boldsymbol{V}_{G_\theta} \boldsymbol{V}^s a \tag{2}$$

The formula uses $\boldsymbol{V}$ as the eigenvector of the graph's normalized Laplacian matrix ($\boldsymbol{V}_{G_\theta} \boldsymbol{V}^s a$), G_θ as the filter function, and a as the graph's signal at the node. Variable G_θ is interpreted as the graph Laplacian matrix's eigenvalue function or $G_\theta(\Lambda)$, where θ represents the function parameter and (Λ) is the diagonal matrix of eigenvalues. It is possible to approximate $G_\theta(\Lambda)$ to lower the computing complexity, and Equations (3-5) determine the calculations.

$$G_\theta(\Lambda) \approx \textstyle\sum_{l=0}^{l} \theta_l' \, s_l(\bar{K}), \tag{3}$$
$$\bar{K} = \frac{2}{\lambda_{Maxi}} K - J_n, \tag{4}$$
$$L = J_n - C^{-(1/2)} X C^{-(1/2)} \tag{5}$$

Variable s_l is the l-order Chebyshev polynomial, G_θ^* is the coefficient vector, K is the graph Laplacian matrix, λ_{Maxi} is L's largest eigenvalue, J_n is the identity matrix, C is the opposite angle matrix ($\bar{X}_{ji}$), and X is an adjacent matrix with j and i layers. The convolutional layer is with l less than or equal to, is shown in Equations (6-8).

$$G_\theta^* a \approx \theta\left(J_n + C^{-(1/2)} X C^{-(1/2)}\right) a, \tag{6}$$
$$\bar{X} = X + J_n, \tag{7}$$
$$\bar{C}_{jj} = \textstyle\sum_i \bar{X}_{ji} \tag{8}$$

The GCN's convolutional layer ($g^{(k)}$) is demonstrated in Equation (9).

$$g^{(k)} = \sigma\left(\bar{C}^{(1/2)}\overline{XC}^{(1/2)}g^{(k-1)}z^{(k-1)}\right) \quad (9)$$

The non-linear activation operation is $\sigma(\cdot)$ and the GCN's weight matrix at $the\ l^{th}$ layer is denoted as $z^{(k-1)}$. GCN is used to model collaborative learning connections. The technology allows for early detection of at-risk learners and reliable forecasting of student involvement and performance trends. The hyperparameter used in the GCN is provided in Table 2.

Table 2. Hyperparameters Used in the GCN

Parameter	Ranges
Number of Graph Layers	2 – 4
Hidden Units per Layer	64 – 256
Learning Rate	0.001 – 0.01
Dropout Rate	0.2 – 0.5
Weight Decay	0.0001

LSTM: A unique RNN for the gradient disappearing and exploding process is LSTM. While LSTM and RNN share a similar unrolled structure, LSTM offers higher levels of data control. It obtains the engagement patterns and temporal activities of the students in the online educational ecosystem. To address the gradually diminishing issues, the forget gate enables the LSTM to reduce the impact of prior state information in the short memory (e_s) and emphasize the residual information of students in the online education ecosystem in the long memory ofH_s. It additionally incorporates the cell state (C_s) memory information, which provides state floating and combines with the input $I(s)$ to the hidden state $H(s)$ through the active functions of $F_1(\cdot)$ as $tanh$ (Δ) and $F_2(\cdot)$ as $sigmoid$ (σ) functions. An LSTM cell (Figure 3) has 2 input gates, a single output gate, and a forget gate.

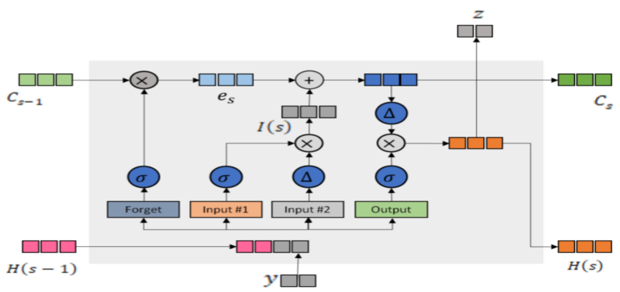

Figure 3. LSTM Cell Unit

Through #1 and #2 gates to provide the input $I(s)$ and the preceding hidden state $H(s-1)$ is evaluated in Equations (10-11).

$$I_1(s) = \sigma(z_{IH}^1 \times I(s) + z_{HH}^1 \times H(s-1) + y_1) \quad (10)$$
$$I_2(s) = tanh(z_{IH}^2 \times I(s) + z_{HH}^2 \times H(s-1) + y_2) \quad (11)$$

Where the state selection is represented by the $tanh$ function, while the sigmoid function (σ) is denoted by$H(s-1)$, and $I_1(s)$ is the input data's $I(s)$ state update z. Equation (12) provides the output of the forget state at the forget gate based on $I(s)$ and $H(s-1)$.

$$F(s) = \sigma(z_{IH}^F \times I(s) + z_{HH}^F \times H(s-1) + y_F) \quad (12)$$

Variable $F(s)$ stands for important knowledge that needs to be maintained in long memory, and irrelevant data are eliminated. The output $(O(s))$ of $I(s)$ and $H(s-1)$ is obtained at the output gate through Equation (13).

$$O(s) = \sigma(z_{IH}^O \times I(s) + z_{HH}^O \times H(s-1) + y_O) \quad (13)$$

Then, the output gate is applied to the cell state $C(s)$ simultaneously, as shown in Equation (14).

$$C(s) = C(s-1) \times F(s) + I_1(s) \times I_2(s) \quad (14)$$
$$H(s) = O(s) \times tanh\left(C(s)\right) \quad (15)$$
$$b(s) = z_{Hb} \times H(s) + y_H \quad (16)$$

Information in both long-term and short $C(s-1)$ memory is utilized by the cell state. The LSTM cell's resulting outcomes, such as $H(s)$ and $b(s)$ with bias y, are determined in Equations (15) and (16). The LSTM mainly determines the temporal behavior and engagement trends of the student by extracting several features from the obtained data. Table 3 represents the LSTM hyperparameters.

Table 3. Hyperparameters of LSTM

Parameter	Ranges
Number of LSTM Layers	1 – 3
Hidden Units	128 – 512
Learning Rate	0.001 – 0.005
Dropout Rate	0.2 – 0.4
Sequence Length	20 – 50
Batch Size	32 – 128

AMB Optimization: One useful metaheuristic algorithm that mimics the observed behavior of monarch butterflies is the Monarch Butterfly (MB) Optimization Algorithm. The MB population is uniform, and a random population made up of possibilities constitutes the initial phase of the MB algorithm. It is used to optimize the hyperparameters presented in the GC-LSTM method. The following method is used to categorize the MB population into two distinct categories: Lands One (l_1) and Two (l_2).

$$l_1 = N_q(1) \times D\left(o \times N_q\right) \quad (17)$$
$$l_2 = N_q - N_q(1) \times N_q(2) \quad (18)$$

The overall number of individuals is denoted by $N_q(1)$ and $N_q(2)$, as shown in Equations (17-18). The value of a surrounding integer (D) that is equal to or larger than the neighboring integer. The ratio of monarch butterflies' (participants or individuals) l_1 to l_2 is denoted by the letter o.

$$W_{j,i}^{s+1} = W_{o1,i}^{s} \quad (19)$$

Equation (19) represents the idea based on the production of an extra population by the parental monarch butterflies, l_1. The element containing the monarch butterfly position at the time over iterations $W_{j,i}^{s+1}$, is provided. The i^{th} element is then updated and represented by $W_{o1,i}^{s}$. The weighted factor and the highest executed stage are denoted by β and m_{Zt} in Equation (20).

$$\beta = \frac{m_{Zt}}{s^2} \quad (20)$$

The influence on $W_{j,i}^{s+1}$ is expected to enhance and fall into the exploration process with the interval (s) while the value β is significant. The AMB optimization is the enhanced form of MB. The AMB optimization is illustrated by utilizing two different methods that address the large time consumption that occurs while the value β is significant, and more efficiently fine-tune the parameters in the GC-LSTM method with low computational cost. Figure 4 displays an algorithmic flow of AMB optimization.

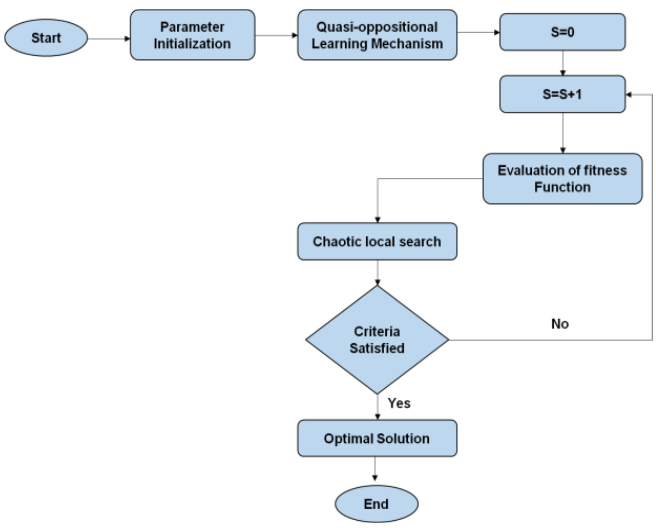

Figure 4. Algorithmic Flow of AMB Optimization

- **Method 1:** Quasi-oppositional learning - This method is required to comprehend the idea of a quasi-oppositional learning process. The oppositional-based method of learning is typically used to increase the accuracy and speed of the solution's convergence. Assuming that dt is the dimensional space that contains the real number as O_n with the range m, n in Equation (21) shows the opposing candidate $\overrightarrow{O_{n(J)}}$.

$$\overrightarrow{O_{n(J)}} = m_j + n_j - O_{n(j)} \quad (21)$$

It is expressed in the following Equation (22) based on a quasi-opposite number.

$$\widehat{O_{n(J)}} = Random\left[\frac{m_j+n_j}{2}\right],\ \overrightarrow{O_{n(J)}} \quad (22)$$

- **Method 2:** Chaotic local search – It is used to address premature convergence. The chaotic mechanism's quantitative expression is presented in Equation (23).

$$(Chao.m)_{K+1}^{dm} = f(Chao.m)_1^{dm} \quad (23)$$

Variable dm represents the dimensional mapping and the value of K variance with function f. The chaotic model is denoted by $Chao.m$. Equation (24) depicts the population's exponential mapping (Ψ_{dm+1}).

$$\Psi_{dm+1} = \rho \times \Psi_{dm} \times (1 - \Psi_{dm}) \quad (24)$$

Variable Ψ_{dm} is the chaotic value, which runs from 0 to 1. The following Equation (25) is used to express the chaotic sequence $(\lambda_{R,n,P})$. The monarch butterfly, based on the chaotic process $(W_{j,i}^{s+1})$, is described as follows using Equation (26).

$$\lambda_{R,n,P} = \rho \times \Psi_{R,n,P}(1 - \Psi_{R,n,P}) \quad (25)$$
$$W_{j,i}^{s+1} = W_{j,i}^{s} + \Psi_{R,n,P} \times \left[sW_L - \frac{1}{2}\right] \quad (26)$$

The system generator quantity, sample count, and iteration number are represented by the variables R, n, and P. It provides an efficient fine-tuning performance with quick functioning, and it reduces the cost of computation. Algorithm 1 represents the AMB-GC-LSTM algorithm. AMB optimization hyperparameters are presented in Table 4.

Table 4. AMB Optimization Hyper-Parameters

Parameter	Ranges
Population Size (N_q)	$20 - 50$
Maximum Iterations (t)	$50 - 200$
Migration Ratio (o)	$0.3 - 0.7$
Weight Factor (β)	$0.1 - 0.9$
Chaotic Map (ρ)	$3.5 - 4.0$

Algorithm 1: AMB-GC-LSTM

```
import numpy as np
import tensorflow as tf
def graph_convolution(X, A,W):
return tf.nn.relu(A_norm, X,W)
def lstm_layer(inputs):
lstm = tf.keras.layers.LSTM(32, return_sequences=False)
return lstm(inputs)
def AMB_optimize(objective_fn, pop_size=10, iterations=20):
population = np.random.rand(pop_size, 5)
best_params, best_score = None, float('inf')
```

```
for t in range(iterations):
population = best_params + 0.1 * np.random.randn
(*population.shape)
return best_params
def train_AMB_GC_LSTM(X, A, Y):
def objective_fn(params):
W = np.random.rand(X.shape[1], 16)
gc_output = graph_convolution(X, A, W)
gc_output = np.expand_dims(gc_output, axis=1)
lstm_output = lstm_layer(gc_output)
pred = tf.keras.layers.Dense(1) (lstm_output)
loss = tf.reduce_mean(tf.square(pred - Y))
return float(loss.numpy())
best_params = AMB_optimize(objective_fn)
print ("Best parameters found:", best_params)
```

Through integrating the LSTM to identify the sequential student's behaviors of the students while GCN is used to capture the student collaboration patterns, the integrated AMB-GC-LSTM method allows intelligent evaluation of detailed educational data, while the AMB optimization enhances the prediction efficiency and accuracy. In digital twin-based online education systems, applications include forecasting of real-time engagement among students, early identification of at-risk students, personalized content recommendations, dynamic performance assessment, and adaptive feedback generation.

The Adaptive Monarch Butterfly Optimization (AMB) algorithm is used to optimize key hyperparameters of the GC-LSTM model, such as learning rate, hidden units, and dropout rate. Unlike traditional methods, AMB efficiently explores the search space using quasi-oppositional learning and chaotic local search. This improves model performance by identifying optimal parameter settings that enhance both spatial (GCN) and temporal (LSTM) feature learning. Additionally, AMB reduces computational cost by avoiding exhaustive search and enabling faster convergence, thereby minimizing training time while maintaining high prediction accuracy.

In the proposed framework, the graph structure is constructed using collaborative learning features, where each student is represented as a node in the graph. Edges between nodes are established based on interaction-related features such as peer interaction count, group activity participation, and collaboration score. These features are used to define the strength of relationships between students, forming the adjacency matrix for the GCN.The resulting graph captures the collaborative learning environment, where strongly connected nodes indicate higher interaction or shared learning behavior. This structure enables the GCN to effectively model peer influence and knowledge sharing, which are important factors in predicting student engagement and performance.

4. Performance Evaluation

The research is primarily intended to develop an efficient real-time digital twin framework for a big data-driven online education ecosystem; thus, it proposes the AMB-GC-LSTM method for continuous prediction of students' behavior and collaborative patterns in the online education ecosystem. The effectiveness of integrating GCN and LSTM is supported by the improved performance of the proposed model compared to existing methods. While LSTM effectively captures temporal behavioral patterns and GCN models collaborative interactions, their individual use may fail to represent both aspects simultaneously. The combined GC-LSTM framework enables joint learning of relational and sequential features, resulting in more accurate prediction of student engagement and performance. This demonstrates that the integration provides a more comprehensive representation of student behavior than single-model approaches. The research used Python as a programming language with 32GB RAM and the TensorFlow library for the implementation performance. This section provides a comprehensive exploration of the proposed AMB-GC-LSTM method's performance.

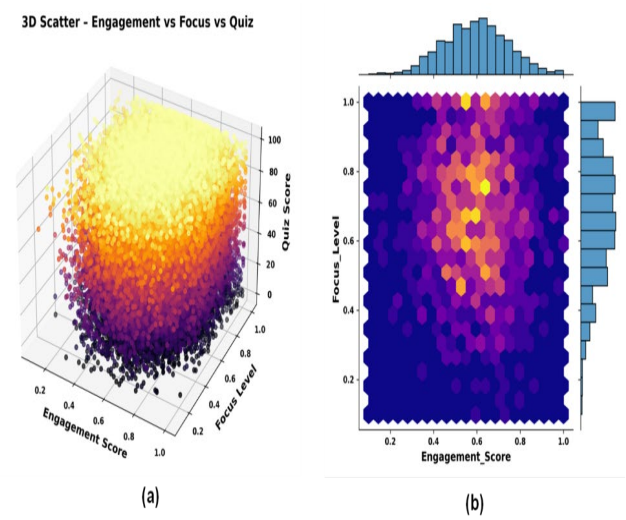

Figure 5. Visual Depiction of (a) Relationship between Engagement Score, Focus Level, Quiz Score, and increasing involvement and focus

The digital twin online learning dataset's relationship between the engagement score, focus level, and quiz score is demonstrated. The proposed method's prediction accuracy for student performance is supported, which reveals dense clusters showing significant positive association (Figure 5(a)), and Figure 5(b) displays the higher quiz performance with the increasing involvement and focus.

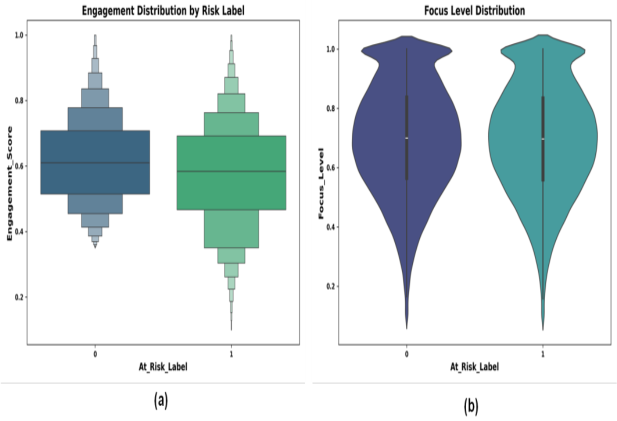

Figure 6. Estimation of (a) Distribution of Engagement and (b) Focus Level Distribution

The distribution of engagement by the risk label in Figure 6(a) demonstrates that at-risk students (label 1) have a lower engagement score with less variance. The focus level distribution shown in Figure 6(b) highlights the attention reduction as a major predictor of academic risk by showing lower median focus among at-risk learners.

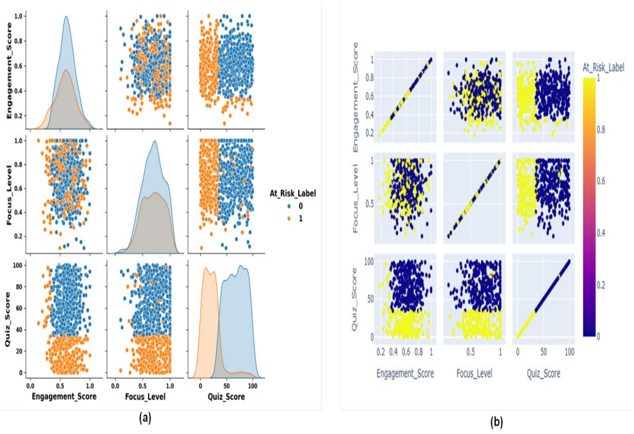

Figure 7. Graphical Representations of (a) At-Risk Learners' Relationship and (b) Correlation Matrix

Figure 7(a) illustrates the relationship between the engagement score, focus level, and quiz score, demonstrating that at-risk learners (label 1) show a greater dispersion, indicating inconsistent engagement, while the non-risk learners (label 0) show high-value clusters. Figure 7(b) correlation matrix supports accurate digital twin forecasting of learning performance by validating the high positive correlations between engagement, focus, and quiz scores.

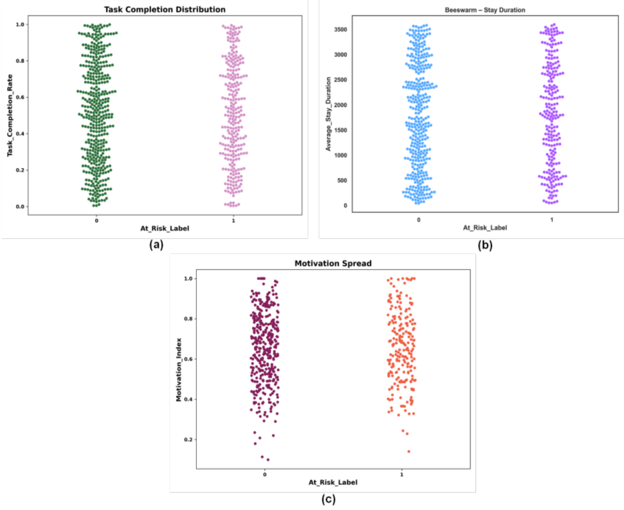

Figure 8. Visual Depiction of (a) Task Completion Distribution, (b) Stay Duration, and (c) Motivation Spread

The task completion distribution in Figure 8(a) demonstrates that non-risk learners regularly achieve better completion rates, indicating a stronger dedication to academics. Figure 8(b) displays the longer average platform involvement among non-risk students in stay duration, which suggests sustained learning focus. Figure 8(c) determines the motivation spread that emphasizes behavioral deterioration effectively captured by the digital-twin predictive method, highlighting lower motivational levels and increased variability for at-risk learners.

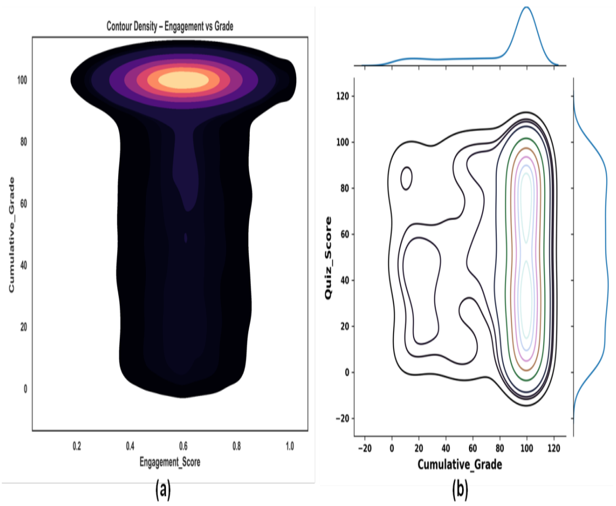

Figure 9. Estimation of (a) Engagement Score vs Cumulative Grade and (b) Grade Reliance on Quiz

There is a concentrated high-quality zone at greater engagement levels in the density of engagement score and cumulative grade in Figure 9(a), suggesting a direct correlation between involvement and academic performance. Figure 9(b) shows significant grade reliance on quiz performance, validating that final grades in the digital twin ecosystem are predicted by consistent evaluations.

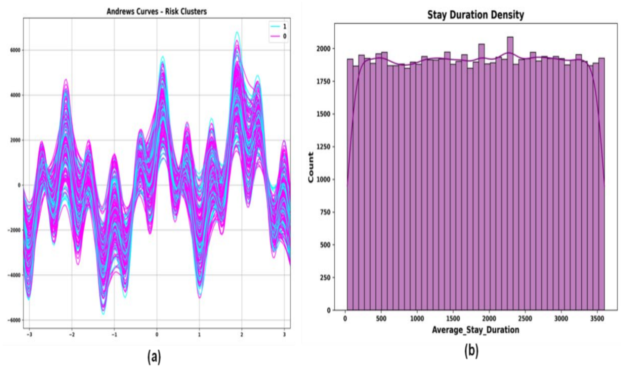

Figure 10. Graphical Depiction of (a) Waveform Divisions among Both Students and (b) Stay Duration Average

Figure 10 (a) displays the clear waveform divisions between at-risk and non-risk students. At-risk student shows erratic oscillations, and non-risk students exhibit smooth patterns. Figure 10(b) illustrates the big data-based online learning environment, consistent participation monitoring through the stay duration average, which highlights the virtually uniform interaction time distribution.
Table 5 represents the proposed AMB-GC-LSTM outcomes in various matrices. The results of the proposed AMB-GC-LSTM method are determined to be more efficient in student engagement (96.8%), learning performance (95.6%), instructor feedback response time (2.9s), resource allocation accuracy (93.9%), teaching efficiency (94.2%), and computational cost (0.73).

Table 5. Illustration of AMB-GC-LSTM outcomes in various matrices

Parameters	Values
Student Engagement (%)	96.8
Learning Performance (%)	95.6
Instructor Feedback Response Time (s)	2.9
Resource Allocation Accuracy (%)	93.9
Early Risk Detection Rate (%)	93.4
Teaching Efficiency (%)	94.2
Computational Cost	0.73

4.1 Comparison Phase

The research proposed the AMB-GC-LSTM method for forecasting the sequential student behavior and collaboration patterns of the students. In this section, the AMB-GC-LSTM is compared with various traditional techniques, including RNN [15], Autoencoder (AE) [15], Graph Neural Network (GNN) [15], Convolutional Neural Networks and LSTM (CNN + LSTM) [15], HDL [18], Multilayer Perceptrons (MLP) [18], Deep Feedforward Neural Networks (DFFNN) [18], Autoencoder [21], LR [21], Support Vector Machine (SVM) [21], and K-Nearest Neighbor (KNN) [21] by employing various performance matrices like recall, accuracy, F1-score and precision (Table 6). Table 7 determines the comparison outcomes of proposed and existing methods with various performance matrices.

Table 6. Performance Matrices and Description

Parameter Definitions	Description
Accuracy is the proportion of accurate real positive and real negative forecasts overall.	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision is the proportion of real positive forecasts over all the positive predictions.	$\frac{TP}{TP+FP}$
The percentage of real positive cases that a prediction method accurately classifies as positive is known as Recall.	$\frac{TP}{TP+FN}$
F1-score is the harmonic mean of precision and recall. It measures the balance between both metrics.	$2 \times \frac{Precision \times Recall}{Precision+Recall}$

Note: TP-True Positives, TN-True Negatives, FN-False Negatives, and FP-False Negatives.

Table 7. Comparison among AMB-GC-LSTM and Exiting Methods

Methods	$Accuracy$	$Precision$	$Recall$	$F1-score$
RNN [15]	0.78	0.77	0.73	0.75
AE [15]	0.81	0.80	0.76	0.78
GNN [15]	0.76	0.75	0.71	0.73
CNN + LSTM [15]	0.85	0.84	0.80	0.82
HDL [18]	0.9567	0.9424	0.9645	0.9378
MLP [18]	0.7141	0.7565	0.7892	0.7685
DFFNN [18]	0.939	0.9123	0.8975	0.9162
Autoencoder [21]	0.84	0.64	0.57	0.59
LR [21]	0.53	0.29	0.32	0.25
SVM [21]	0.58	0.41	0.39	0.35
KNN [21]	0.38	0.34	0.32	0.27
AMB-GC-LSTM [Proposed]	0.965	0.945	0.974	0.959

The suggested AMB-GC-LSTM method achieved 0.965 of accuracy and 0.945 of precision, outperforming other existing methods. According to the findings, the accuracy and precision of the proposed method are superior to those of the traditional methods in predicting student behaviors in the online educational ecosystem (Figure 11).

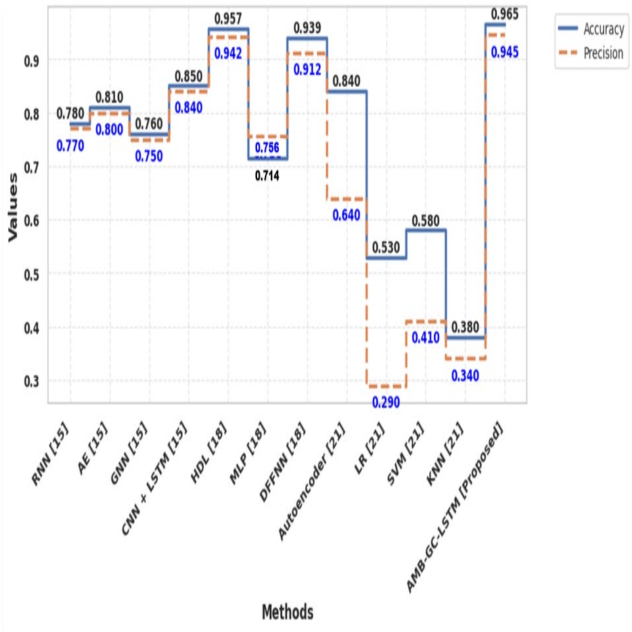

Figure 11. Accuracy and Precision Outcomes of AMB-GC-LSTM and Traditional Techniques

The proposed AMB-GC-LSTM method explores 0.959 of F1-score and 0.974 of recall and it has significant results compared to traditional methods. Given the complexity of the AMB-GC-LSTM model, interpretability is essential for practical adoption by educators and administrators. The proposed framework supports interpretability by associating model predictions with key input features such as engagement levels, interaction frequency, and performance trends. For instance, when a student is identified as at-risk, the system can highlight contributing factors such as low participation or declining performance. These insights can be presented through intuitive dashboards and visual indicators, enabling non-technical users to understand the reasoning behind predictions and take appropriate actions. This improves transparency, trust, and usability of the system in real-world educational settings. Based on the results, the proposed AMB-GC-LSTM method outperforms all the existing techniques in forecasting the students' behaviors in online education (Figure 12).

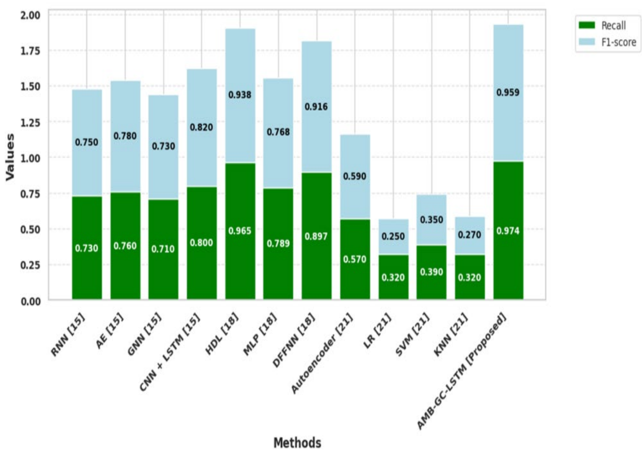

Figure 12. Comparison Results of Proposed and Existing Methods with Recall and F1-score

5. Discussion

The proposed framework can be integrated into existing Learning Management Systems (LMS) by connecting with platform data sources such as student activity logs, assessment records, and interaction data through application programming interfaces (APIs). The model can operate as a backend analytics module that continuously processes incoming data and generates predictions related to student engagement and at-risk status. The proposed system is designed to adapt to dynamic changes in online education environments. Variations in student learning patterns are addressed through continuous model updates, allowing the system to learn from newly observed behavioral data and adjust predictions accordingly. Changes in course structures, such as new content formats or assessment strategies, can be incorporated by updating input features and retraining the model to reflect current learning conditions. Additionally, the framework supports integration with evolving technologies and platforms through flexible data interfaces, ensuring compatibility with new tools and systems. This adaptability enables the model to remain effective and reliable in continuously changing educational settings.

The research proposed a real-time digital twin with a big data-based method called AMB-GC-LSTM for predicting the behaviors of the students in an online educational ecosystem. There were several existing methods compared with the proposed technique, and they show numerous limitations, including the RNN [15], AE [15], GNN [15], and CNN+LSTM [15], which were frequently inadequate in capturing the dynamic student behaviors and the collaborative exchanges in real-time. Sequential or time-dependent patterns were unable to be addressed by the HCL [18], MLP [18], and DFFNN [18]. In a large-scale real-time online learning ecosystem, the autoencoder [21], LR [21], SVM [21], and KNN [21] explored the constraints with adaptability and precise predictions. The results of the proposed framework can be directly translated into practical educational actions. For instance, when the model identifies a decline in student engagement or predicts at-risk behavior, instructors can provide timely feedback, assign additional learning resources, or modify instructional strategies. Similarly, system designers can integrate automated alerts and adaptive recommendation systems that guide students based on their real-time performance. These actionable insights enable proactive intervention, improve student retention, and support personalized learning pathways in online education environments. Personalized learning and integration of multi-relational educational data were the issues associated with the traditional techniques. By accurately modeling the constant student behaviors and collaborative learning relationships in real-time, the proposed AMB-GC-LSTM method resolves the existing constraints. The AMB improves the forecasting accuracy, scalability, and adaptability by optimizing the parameters, while the AMB-GC-LSTM supports a dynamic, expensive, and varied online education system by facilitating at-risk learner's detection, individualized learning recommendations, and effective resource allocations. Real-time dashboards and adaptive recommendation systems provide actionable insights for students, educators, and administrators, supporting personalized learning pathways and resource allocation.

The proposed AMB-GC-LSTM framework has significant practical implications for real-time online education systems. By continuously analyzing student interaction and performance data, the model enables timely prediction of engagement levels and early identification of at-risk learners. This allows instructors to take immediate actions, such as providing personalized feedback, recommending learning resources, or adjusting teaching strategies. As a result, the system supports proactive decision-making, improves student retention, and enhances overall learning effectiveness in dynamic educational environments.

In addition to improving student engagement and performance prediction, the proposed framework plays a significant role in supporting instructors in adaptive teaching. By providing real-time insights into student behavior and engagement levels, the system enables instructors to adjust their teaching strategies, such as modifying content delivery, offering targeted feedback, and designing personalized learning activities. Furthermore, early identification of at-risk learners allows instructors to implement timely interventions, such as one-on-one support or supplementary materials.

5.1 Limitations and Future Directions

The proposed digital twin method is constrained by its need to enhance its adaptability, robustness, and scalability for larger online educational ecosystems and other intelligent learning environments. Future research will be able to explore the integration with heterogeneous data sources, compact designs for resource-limited environments, multi-model assessment, and cross-domain applications.

Although the proposed model effectively analyzes student behavior within the online platform, external factors that influence learning outcomes are not explicitly considered. These include aspects such as students' socio-economic background, internet accessibility, learning environment, and individual motivation. Such factors may significantly impact engagement and academic performance but are not captured in the current dataset. Future work can incorporate these external variables to further enhance the robustness and generalizability of the model.

The proposed model may be influenced by potential biases present in the dataset, such as imbalanced demographic representation or variations in student participation levels. These biases can affect the model's predictions, particularly in identifying at-risk students, where certain groups may be overestimated or underestimated.

While the proposed framework demonstrates strong predictive performance, feedback from educational stakeholders such as teachers, administrators, and students has not been explicitly incorporated in the current study. Evaluating the system's usability and effectiveness through real-world user feedback is essential for practical deployment. Future work will focus on conducting user studies and collecting stakeholder feedback to assess system usability, interpretability, and overall impact on teaching and learning processes.

6. Conclusions

The quick growth of online learning platforms presented particular possibilities for individualized instruction, with difficulties for monitoring the student behaviors instantly. To improve learning and teaching efficacy, the research suggested a real-time digital twin with a big data-based online education ecosystem called AMB-GC-LSTM that continuously captured and forecasted huge quantities of educational information. The digital twin online learning dataset was obtained and preprocessed by the data cleaning and z-score normalization techniques to clean and normalize the information. The proposed AMB-GC-LSTM method is efficiently applied to the student's behavior in online educational ecosystem forecasting performance. Comparisons among the proposed and existing methods were conducted, and the proposed method showed more precision (0.945), accuracy (0.965), F1-score (0.959) and recall (0.974) than the conventional techniques using Python as an implementation tool. It highlighted that the proposed method provided an intelligent, adaptable, and scalable online learning ecosystem that enabled continuous education and skill development. Beyond performance improvements, this study highlights the importance of integrating relational and temporal learning for understanding complex student behaviours in online education. The proposed framework demonstrates how combining graph-based and sequential modeling with real-time data can enable more adaptive and intelligent learning systems. These insights contribute to the development of next-generation educational technologies that support proactive intervention, personalized learning, and scalable digital learning environments.

Declarations

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

Code availability: Not applicable.

Authors' Contributions: Yanyu Qian is responsible for designing the framework, analyzing the performance, validating the results, and writing the article. Na Zhang is responsible for collecting the information required for the framework, provision of software, critical review, and administering the process.

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