SCIENTIFIC OASIS

Decision Making: Applications in Management and Engineering

Journal homepage: www.dmame-journal.org
ISSN: 2560-6018, eISSN: 2620-0104

Utilising an Interactive Deep Learning Framework to Enhance the Effectiveness of Intelligent Teaching Practices

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ARTICLE INFO

Article history:
Received 14 August 2024
Received in revised form 19 Dec 2024
Accepted 20 January 2025
Available online 10 February 2025

Keywords:
Sustainable entrepreneurship, vocational education, artificial intelligence, green innovation, decision-making framework

ABSTRACT

Conventional teaching methodologies often fail to accommodate the diverse needs and learning styles of individual students, presenting a persistent challenge in education. This study proposes an innovative interactive deep learning framework that transforms intelligent teaching practices by integrating recurrent neural networks (RNNs). By leveraging the temporal modelling capabilities of RNNs within an interactive instructional environment, the framework dynamically analyses sequential patterns in student learning and engagement. A key contribution of this research is the development of a dynamic approach that utilises RNNs to model long-term dependencies and temporal dynamics within educational processes. This enables intelligent teaching systems to adapt in real time to students' behavioural patterns and evolving learning trajectories. Additionally, the incorporation of real-time feedback mechanisms allows educators to intervene and refine instructional strategies based on predictive insights generated by RNNs. This iterative and interactive process fosters a highly personalised learning experience, enhancing student engagement and knowledge retention. Empirical evaluations in real-world educational settings confirm the framework's efficacy, demonstrating substantial improvements in teaching effectiveness and student learning outcomes. This study advances the development of adaptive and responsive intelligent teaching systems capable of delivering personalised instruction on a large scale. It makes a significant contribution to educational technology by introducing a transformative interactive deep learning framework enhanced by RNNs, ad-dressing the critical issue of personalisation in education while providing a scalable solution to improve intelligent teaching methodologies and student learning experiences.

1. Introduction

Effective teaching practices play a pivotal role in shaping the educational landscape, directly influencing student learning experiences and outcomes across various disciplines and academic levels. In an era characterised by rapid technological advancements and an expanding knowledge

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https://doi.org/10.31181/dmame8120251333

base, the demand for innovative teaching methodologies has intensified [1]. These approaches must accommodate the diverse needs and learning styles of students. While traditional teaching methods pro-vide a foundational framework, they often struggle to adapt to the evolving educational environment [2]. A primary limitation of conventional teaching approaches is their inability to address the varied learning styles of students [3-4]. Learners come from diverse backgrounds, possess different levels of prior knowledge, and progress at varying rates. Consequently, a universal teaching method often fails to engage students effectively or meet their individual learning needs [5], resulting in suboptimal educational outcomes. Furthermore, the process of knowledge acquisition necessitates a more dynamic and adaptable instructional approach—one that seamlessly integrates new information into the curriculum while simultaneously adjusting teaching strategies in real time.

The integration of artificial intelligence (AI) into educational settings has garnered significant attention due to its potential to personalise learning experiences [6]. AI-driven systems leverage databased insights into student behaviour, preferences, and learning trajectories to enhance instruction [7-9]. Among AI techniques, recurrent neural networks (RNNs) have emerged as powerful tools for analysing sequential data [10-13], demonstrating particular efficacy in recognising and modelling learning patterns in educational contexts. Designed specifically for sequential data processing, RNNs differ from conventional feedforward neural networks by incorporating recurrent connections that enable them to retain memory of previous inputs [14-15]. This capability allows them to identify temporal dependencies and patterns within sequential datasets [16-18], making them particularly relevant in educational environments. Learning is an incremental process influenced by multiple factors, including prior knowledge, instructional strategies, and individual learning preferences [19-20]. By effectively modelling these sequential dynamics, RNNs offer a promising solution for enhancing adaptive and personalised teaching methodologies.

Numerous studies have highlighted the effectiveness of RNNs in various educational applications [21], including natural language processing (NLP), student performance prediction, and adaptive learning systems. In intelligent tutoring systems (ITSs), RNNs have been employed to simulate student interactions by predicting learning outcomes based on sequential behavioural patterns [22]. Furthermore, RNNs have been utilised to analyse and generate personalised feedback, facilitating adaptive learning experiences tailored to individual student needs [23]. Despite these advancements, a significant gap remains in the literature concerning the application of RNNs to enhance intelligent teaching practices [24]. While RNNs have been integrated into educational contexts, their potential for dynamically adapting teaching strategies remains largely unexplored [25]. The majority of existing research has focused on developing technology-driven solutions without adequately considering how RNNs can contribute to improving teaching effectiveness [26]. This narrow focus limits the understanding of RNNs as tools for enhancing intelligent teaching methodologies and restricts the identification of areas for further development [27].

This research introduces an innovative interactive deep learning framework that harnesses the temporal modelling capabilities of RNNs within an interactive teaching environment. The proposed approach aims to transform intelligent teaching practices by integrating RNNs with interactive teaching interfaces, creating dynamic and adaptive systems capable of responding in real time to student behaviours and evolving learning trajectories. A key contribution of this study is the development of a dynamic system that employs RNNs to capture and analyse sequential patterns in student interactions and learning progressions. By effectively modelling long-term dependencies and temporal dynamics inherent in educational processes, the proposed framework enables intelligent teaching systems to adapt to individual student needs in real time, addressing the critical issue of personalisation in education [6]. Additionally, the framework incorporates a real-time feedback system that allows educators to intervene and modify instructional strategies based on RNN-generated predictions. This interactive and iterative process fosters a highly personalised learning experience, enhancing student engagement and knowledge retention [28] (Figure 1).

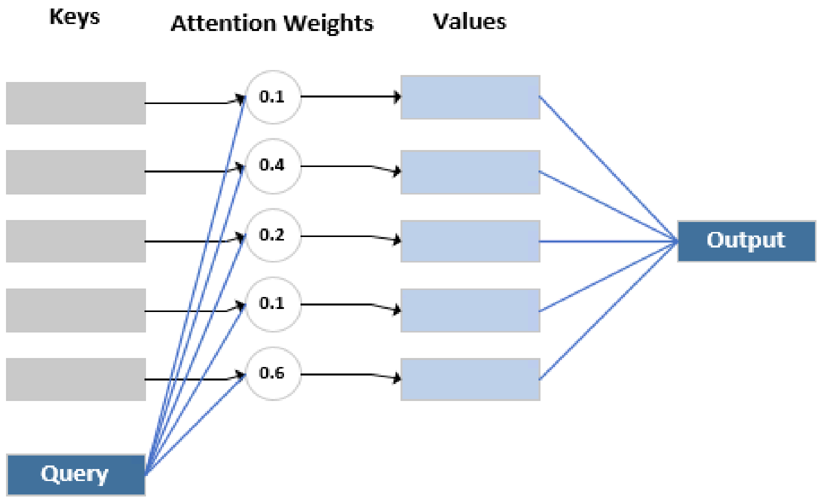

Fig.1. Attention Weight

Empirical evaluations conducted in real educational settings confirm the effectiveness of the proposed approach, demonstrating notable improvements in teaching efficacy and student learning outcomes [29]. By leveraging RNNs within an interactive framework, this research establishes a foundation for responsive and adaptive intelligent teaching systems capable of delivering personalised instruction on a large scale [30]. The findings of this study hold significant implications for educational practices, as RNNs facilitate a deeper understanding of the factors influencing student engagement, performance, and overall learning experiences [31]. By analysing sequential data, educators can design more effective and personalised teaching methodologies tailored to individual student needs and preferences, thereby enhancing educational outcomes across diverse learning environments [32].

This research seeks to bridge the existing gap in the literature by developing an RNN-based framework to enhance intelligent teaching practices. Specifically, it utilises RNNs to analyse sequential data related to student interactions, learning progressions, and instructional interventions, providing insights into the impact of intelligent teaching strategies on student learning outcomes. The study aims to address the following research questions:

a) How can RNNs be utilised to analyse sequential data and enhance intelligent teaching practices?
b) What are the key components and features of an RNN-based framework for adapting intelligent teaching practices based on student engagement, performance, and overall learning experience?

To achieve these objectives, an RNN model is established to process sequential educational data, encompassing student interactions, performance metrics, and instructional interventions. Existing datasets from online learning platforms are utilised to train and validate the model. The RNN analyses sequential patterns in student data and predicts learning outcomes based on intelligent teaching strategies. Empirical studies are conducted in real educational environments to assess the effectiveness of the RNN-based framework. These studies evaluate the impact of intelligent teaching practices on student learning outcomes. The methodology developed in this research serves as a foundation for future investigations exploring the application of RNNs in educational research and practice [33].

The key contributions of this study include:

- The development of a novel framework that leverages RNNs to enhance intelligent teaching practices in educational settings.

- The utilisation of RNNs to analyse the outcomes of intelligent teaching strategies, offering valuable insights into factors influencing student engagement.
- The establishment of a methodology that can serve as a foundation for future research into the application of RNNs in education.

The subsequent sections of this research article provide an in-depth exploration of the methodology and evaluation of the proposed framework. Section 2 presents a comprehensive literature review, highlighting the growing role of AI in educational technology and discussing the potential of RNNs in analysing sequential data. Section 3 elaborates on the proposed framework, describing the model structure, operational mechanisms, and integration of RNNs with real-time feedback systems to address the research problem. Section 4 outlines the experimental setup used for training and testing the RNNs with a pre-processed educational dataset. Finally, the results are presented, followed by a critical discussion assessing the performance of the proposed framework and its implications for enhancing intelligent teaching practices.

2. Literature Review

According to research on AI and education, AI is becoming more important in personalising learning and improving outcomes [25-26]. AI is revolutionising education by providing creative solutions for varied student demands and learning styles. One key area of AI application in education is adaptive learning systems, which dynamically adjust instructional content and pacing based on individual student performance and preferences. Research has demonstrated the effectiveness of these systems in improving student engagement and knowledge acquisition [6- 27] by providing personalised feedback and tailored learning pathways. ITSs represent another critical AI application in education, designed to offer individualised instruction and support [28]. Studies highlight the benefits of ITSs in facilitating mastery learning and promoting conceptual understanding through personalised tutoring strategies [29]. By integrating AI techniques such as NLP and machine learning, ITSs adapt to students' needs, delivering real-time feedback and guidance to enhance learning outcomes [24-25- 30].

Additionally, AI-powered educational platforms have been developed to support collaborative learning environments [31], fostering interactive engagement among students [32]. Research has explored the role of AI-driven collaborative learning platforms in promoting peer interaction and knowledge sharing [33], leading to improved learning outcomes and strengthened social cohesion among students [34-36]. Beyond ITSs and adaptive learning systems, AI has been employed in various educational applications, including content recommendation, learning analytics, and assessment automation. AI-driven learning analytics have proven effective in generating actionable insights into student performance and engagement [37], enabling educators to make data-informed instructional decisions [38]. Among AI methodologies, RNNs have emerged as powerful tools for analysing sequential data, making them particularly well-suited for educational applications. They are highly effective at understanding and simulating student learning patterns [39]. Unlike conventional feedforward neural networks, RNNs incorporate recurrent connections, allowing them to retain a memory of past inputs [40]. This capability enables the modelling of temporal dependencies and patterns in sequential data, which is essential for analysing student interactions, learning trajectories, and behavioural trends over time.

Several studies have explored the application of RNNs in education, focusing on areas such as student performance prediction, learning behaviour analysis, and educational content recommendation [41]. By examining temporal dependencies in student data, RNN models can generate accurate pre-dictions of future performance outcomes, facilitating early intervention and support strategies. Similarly, research has explored the application of RNNs in analysing learning behaviour patterns by processing sequential data related to student interactions in online learning environments. This includes examining navigation patterns and engagement metrics, allowing the model to identify fundamental behavioural trends and discern how students engage with learning materials [42]. RNNs have also been utilised in educational content recommendation systems, enhancing personalised learning experiences and student engagement. By analysing sequential patterns in student interactions with learning materials, RNNs generate tailored content recommendations based on in-dividual learning preferences and performance metrics [43]. This approach not only improves student engagement but also enhances knowledge retention in online learning environments.

Intelligent teaching practices encompass various instructional interventions and pedagogical strategies aimed at enhancing learning outcomes through data-driven instruction, personalised feedback, and adaptive learning approaches [44]. Data-driven instruction leverages student performance data and learning analytics to inform instructional decisions, identify areas of student need, and tailor teaching strategies to individual learning styles. Personalised feedback [45] provides students with timely, targeted insights into their progress, enabling them to reflect on their learning and adjust their study habits. Adaptive learning strategies [46] dynamically adjust instructional content and pacing based on student mastery levels, fostering a more customised and responsive learning experience. Empirical studies have demonstrated the effectiveness of these intelligent teaching practices in improving learning outcomes across diverse educational contexts. Data-driven instruction has been shown to significantly enhance student achievement and engagement, particularly among learners with varied educational needs and backgrounds [47]. Similarly, personalised feedback has been highlighted as a key factor in promoting student motivation, self-regulation, and academic success [48].

Given these limitations, there is a pressing need for more nuanced and comprehensive approaches to evaluating teaching effectiveness. Advanced technologies, including AI and deep learning, can provide educators with deeper insights into the impact of intelligent teaching strategies, enabling them to make data-informed instructional decisions. Through rigorous empirical studies, researchers can contribute to the development of evidence-based practices that enhance teaching effective-ness and improve educational outcomes. While extensive research has examined the use of RNNs in educational settings [49-50], a gap remains in their application to evaluating intelligent teaching practices. Existing studies on RNNs in education have primarily focused on student performance prediction, learning behaviour analysis, and content recommendation, often overlooking their broader implications for teaching effectiveness. One study, for instance, demonstrated the effectiveness of RNNs in predicting student dropout rates based on sequential engagement metrics [51] but did not directly assess the impact of teaching strategies on student outcomes.

This gap presents an opportunity for our research to contribute to the field by developing an RNN-based framework specifically designed to evaluate intelligent teaching practices. By leveraging RNNs to analyse sequential data—encompassing student interactions, learning progressions, and instructional interventions—this study aims to provide a more comprehensive understanding of how teaching strategies influence learning outcomes. This approach bridges the gap between data-driven analysis and instructional effectiveness, informing the design and implementation of more effective teaching methodologies. Existing studies applying RNNs in education have often focused on tasks unrelated to teaching effectiveness, such as analysing text-based student responses in online learning contexts [34-35]. A synthesis of the reviewed literature establishes a strong foundation for our research, which aims to assess intelligent teaching practices using RNNs within educational settings. Previous research has demonstrated the effectiveness of RNNs in analysing sequential data related to student interactions, learning patterns, and behaviour. RNNs have been shown to be highly proficient in predicting student performance, analysing learning behaviours, and recommending educational content [52-53].

However, the specific application of RNNs in evaluating the efficacy of intelligent teaching practices remains underexplored. Existing studies have primarily focused on related but distinct tasks, failing to directly assess the impact of teaching strategies on student outcomes. This research seeks to address this gap by developing an RNN-based framework specifically designed to evaluate intelligent teaching practices. By analysing sequential data, our study aims to provide a deeper understanding of how instructional interventions, learning progressions, and student interactions are influenced by teaching strategies. This contribution advances the field by informing the development of more effective teaching methodologies, thereby enhancing educational outcomes.

3. Parametric Optimisation of the Food Packaging Process

3.1 A Set of Acceptable Solutions for the Structure of Food Packaging

For this study, a dataset was acquired from [54], originating from a digital education platform. It comprises student interaction logs, performance metrics, and instructional interventions, structured as sequential data representing student engagement with educational resources. These resources include video lectures, quizzes, and discussion forums. Additionally, the dataset incorporates performance metrics such as quiz scores, assignment submissions, and time spent on tasks. It also includes instructional interventions, encompassing individualised feedback from instructors and the adaptive learning techniques employed by the platform. During the data collection process, the online learning platform’s database was accessed, and SQL queries were executed to extract relevant data points. A series of pre-processing procedures were applied to clean and prepare the data for input into the RNN model. Duplicate entries were removed, missing values were addressed, and numerical features were normalised to ensure data accuracy and consistency. Text-based data, including student responses to open-ended questions and discussion forum posts, underwent additional pre-processing. NLP techniques such as tokenisation, stemming, and lemmatisation were implemented to extract meaningful features and reduce dimensionality. Furthermore, categorical variables, including course categories and student demographics, were transformed into numerical representations suitable for the RNN model using either one-hot encoding or label encoding (Table 1). Subsequently, the dataset was divided into training, validation, and test sets, with 70% allocated to training, 15% to validation, and 15% to testing. This ensured that the model was trained on a representative sample while allowing for an assessment of its generalisation performance on unseen data. Ultimately, the pre-processed dataset was prepared for input into the RNN model for training and evaluation.

Table 1
Dataset Characteristics and Features

Characteristic	Feature	Description
Numerical	Timestamp	The time when the interaction occurred
	Content ID	Unique identifier for the content
	User ID	Unique identifier for the user
Categorical	Content Type	Type of content (e.g., question, lecture)
	User Type	Type of user (e.g., student, teacher)
Target	Answered Correctly	Binary variable indicating whether the user answered the question correctly (1) or incorrectly (0)

3.2 Gated Recurrent Units (GRUs) in RNN Model

In this study, GRUs are employed as the core architecture of the RNN model, as illustrated in Figure 2. GRUs address the limitations of traditional RNNs, particularly the vanishing gradient problem and the challenge of capturing long-term dependencies in sequential data. The architecture of a GRU incorporates specialised gating mechanisms that regulate information flow, allowing the model to retain and selectively update relevant information over time. As depicted in Figure 2, a GRU consists of two primary gates: the update gate, which determines the proportion of the previous state to be preserved, and the reset gate, which controls the extent to which new input is integrated into the current state. These mechanisms enable GRUs to capture temporal dependencies more effectively than conventional RNNs, facilitating the simulation of long-term dependencies by selectively updating and retaining information based on the context of the input sequence.

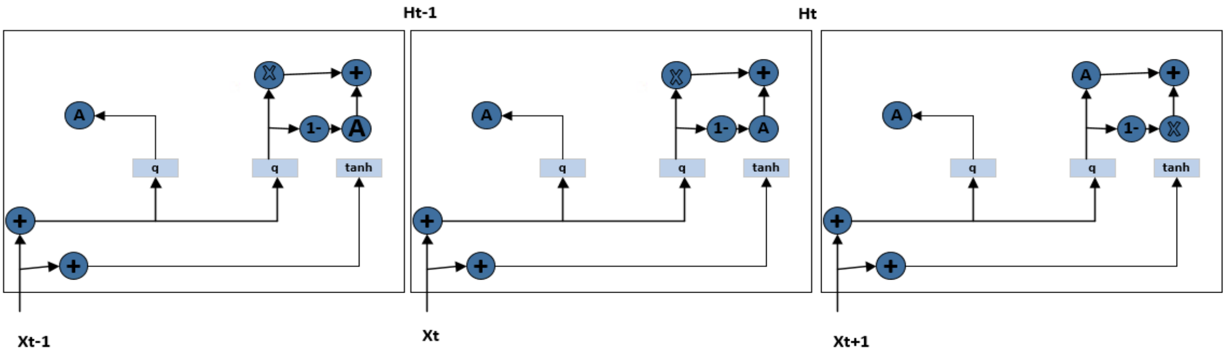

Fig.2. Recurrent Gate Cell

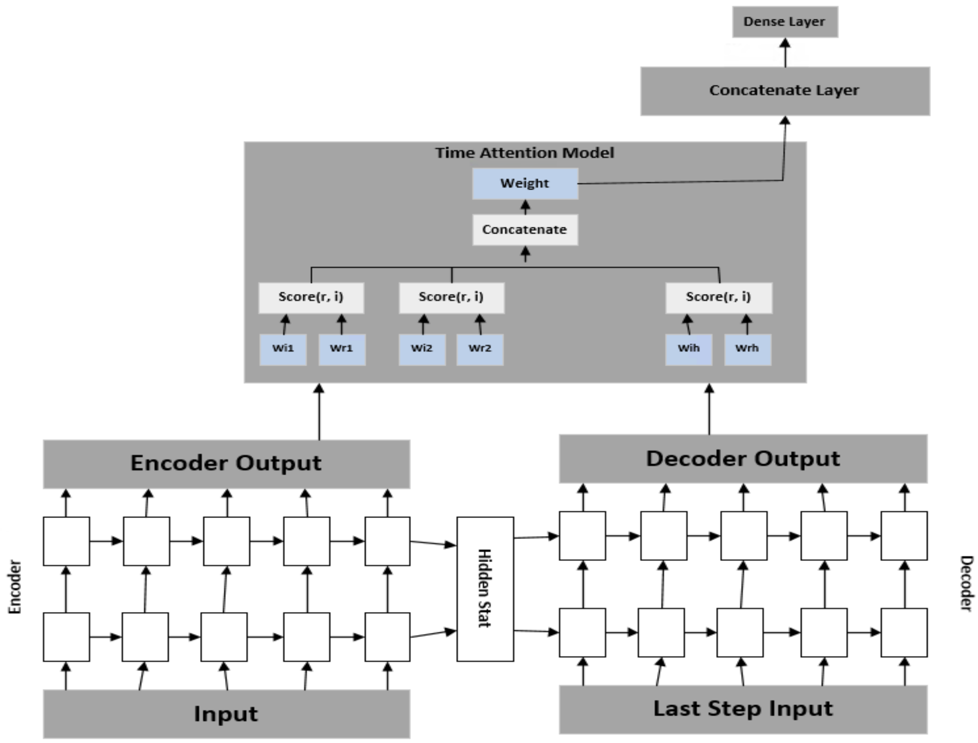

Fig.3. Time Attention

GRUs are particularly suited to this study's RNN model, efficiently processing student interaction data, performance metrics, and instructional interventions. Their ability to handle sequential data allows for the effective modelling of the temporal progression of instructional interventions and student interactions with learning materials. This enables the identification of sequential patterns and learning dynamics over time.

By incorporating GRUs within the RNN model, this study aims to extract valuable insights into the effectiveness of intelligent teaching practices through a de-tailed analysis of sequential data. The gated nature of GRUs allows the model to adaptively update and retain relevant information, enhancing its ability to capture complex relationships between student interactions, instructional interventions, and learning outcomes. Empirical studies [54-55] have demonstrated the efficacy of GRUs in various sequential modelling tasks, providing evidence of their capacity to process sequential data efficiently and capture long-term dependencies. Building on these findings, GRUs are integrated into the RNN framework, as shown in Figure 3, to ad-dress the specific challenges of this research. This enhances the model's ability to assess and evaluate intelligent teaching practices in educational environments.

3.3 Proposed Model Structure

In the proposed framework, illustrated in Figure 4, RNNs with GRUs are employed to assess intelligent teaching practices. The model structure is designed to align closely with the sequential nature of the educational dataset, which includes student interactions, performance metrics, and instructional interventions. The framework leverages GRUs' ability to retain and selectively update information over time, enabling a more comprehensive analysis of how instructional interventions influence student learning outcomes.

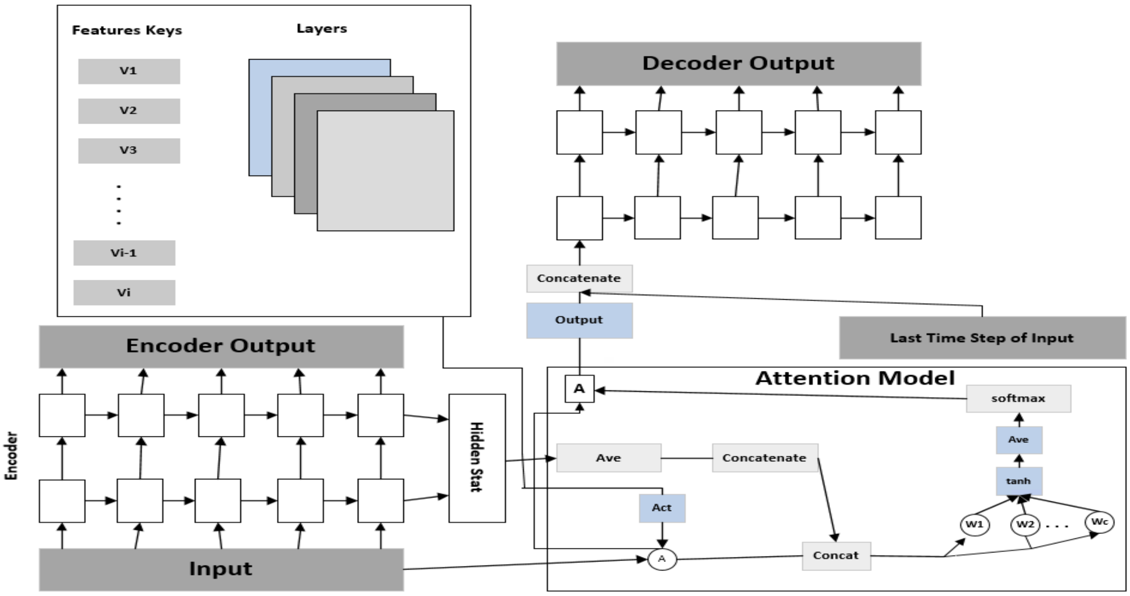

Fig.4. Time Attention

3.4 Model Architecture

Figure 3 shows the input, hidden, and output layers of the RNN model with GRUs. In Figure 2, at each time step t, the input Xt is fed into the model, along with the previous hidden state Ht-1. The GRUs within the hidden layers process the input and hidden states to compute the updated hidden state Ht, which encapsulates the learned representations of the sequential data.

3.4.1 Model Components and Feature Extraction

The model components are structured to extract key features from the educational dataset and represent them as vectors, which are then fed into the model at each time step t. Each feature encapsulates distinct aspects of student interactions, performance metrics, and instructional interventions. This structured representation enables the model to learn meaningful patterns, capturing the temporal dependencies within the data. By leveraging these feature representations, the RNN with GRUs effectively analyses the sequential nature of learning processes, facilitating a deeper understanding of the impact of intelligent teaching strategies on student outcomes.

3.4.2 Input Layer

The input layer functions as the gateway for the dataset, receiving extracted features represented as vectors (Figure 5). Each feature vector encapsulates distinct aspects of the educational data, including student interactions (e.g., time spent on tasks, engagement levels), performance metrics (e.g., quiz scores, assignment grades), and instructional interventions (e.g., personalised feedback, adaptive learning strategies). By structuring the input in this manner, the model effectively captures the temporal dependencies and sequential patterns essential for evaluating the impact of intelligent teaching practices on student learning outcomes.

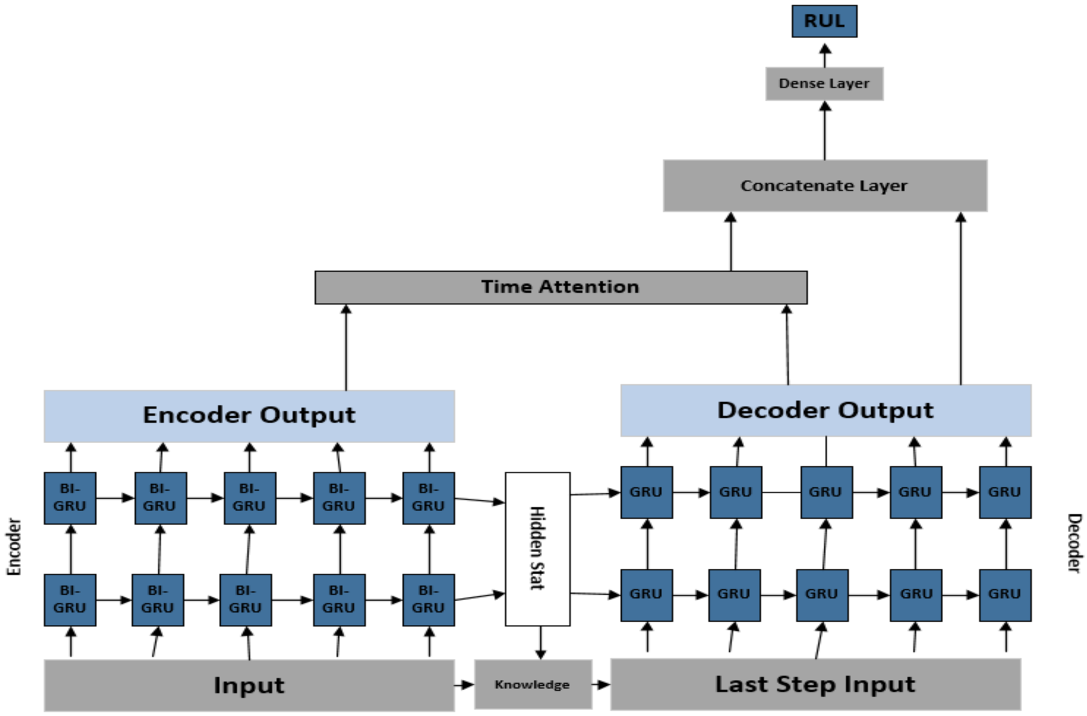

Fig.5. Encoder-Decoder Architecture

The input layer processes these feature vectors and transmits them to the hidden layers, where further computations take place. These hidden layers, incorporating GRUs, capture temporal dependencies and sequential relationships within the data.

Input Layer:

$$X\_t, H\_t = \text{Input and Hidden State at time step} \quad (1)$$

3.4.3 Hidden Layers

The hidden layers incorporate GRUs, which perform computations to update the hidden state based on the input and the previous hidden state. At each time step t, the GRUs integrate the input feature vectors with the prior hidden state to generate the updated hidden state. These GRUs employ specialised gating mechanisms, namely update and reset gates, to regulate the retention and modification of relevant information over time. Such mechanisms enable the model to capture temporal dependencies and recognise sequential patterns within the data, thereby enhancing its ability to learn from the structured progression of student interactions and instructional interventions.

Hidden Layers (GRUs):

$z_t = \sigma\left(W_{zx}X_t + W_{zh}H_{t-1} + b_z\right)$ (Update Gate)

$r_t = \sigma\left(W_{rx}X_t + W_{rh}H_{t-1} + b_r\right)$ (Reset Gate)

$H_t^{'} = \tanh\left(W_{hx}X_t + W_{hh}\left(r_t \odot H_{t-1}\right) + b_h\right)$ (Hidden State Candidate)

$H_t = \left(1 - z_t\right) \odot H_{t-1} + z_t \odot H_t^{'}$ (Hidden State)

3.4.4 Output Layer

The output layer generates predictions by leveraging the learned representations from the hidden layers. It consists of a single unit for regression tasks, such as predicting student performance, and multiple units for classification tasks, such as categorising student engagement levels, depending on the specific objective. This layer consolidates the information extracted from the hidden layers and produces the final output based on the model's learned representation of the input data.

Output Layer:

$Y_t = Output\ at\ time\ step\ t$

3.4 Feature Representation

This study encodes each feature from the educational dataset as a vector, with its elements representing the relevant information embedded within the feature. Numerical features, such as quiz scores or time spent on tasks, are directly incorporated as numerical values within the vector. Categorical variables, including student demographics or course classifications, are typically represented using one-hot encoding or label encoding, where each category is assigned a unique numerical value or binary indicator. Additionally, textual features, such as student responses to open-ended questions or instructional content, are processed using NLP techniques, such as word embeddings or bag-of-words models, to capture semantic information while reducing dimensionality.

3.5 Feature Representation

The research methodology involves processing input data through the RNN model with GRUs at each time step t, systematically analysing the educational data and updating the hidden state based on both the current input and the preceding hidden state.

3.6.1 Initialisation

At the initial time step t=0, the hidden state H0 is either initialised to zero or assigned a random weight, contingent upon the model architecture, and the input features Xt are introduced to the model to initiate the sequential processing.

3.6.2 Sequential Processing

The model accepts input features Xt representing the current educational data at each time step t and combines them with the prior hidden state Ht-1 to update Ht using the GRUs in the hidden layers. The update and reset gates, zt and rt, regulate information flow inside the GRUs to determine how much of the prior hidden state and fresh input is incorporated into the updated hidden state.

3.6.3 Hidden State Update

The updated hidden state Ht encapsulates the learned representations of the sequential data up to time step t, incorporating information from previous interactions and interventions, with the hidden state serving as a memory of past interactions and interventions, enabling the model to capture temporal dependencies and sequential patterns in the educational data.

3.6.4 Output Generation

Based on the hidden layers' representations, the model outputs Yt at each time step t, which may indicate student success metrics in the tasks listed above.

3.6.5 Iterative Process

These steps are repeated for each time step t until the entire sequence of input data is processed, allowing the RNN with GRUs to dynamically analyse sequential educational data and generate insights into the effectiveness of intelligent teaching methodologies.

4. Experiments

The experimental setup for training and assessing GRUs using the pre-processed educational dataset is described here. The goal is to evaluate the proposed framework for evaluating intelligent teaching techniques in real-world education.

4.1 Data Splitting

Three sets were created using the pre-processed educational dataset: a training set for model training, a validation set for hyperparameter optimisation and model selection, and a testing set for GRU model performance evaluation.

4.2 Model Training

The GRU model was trained using the training dataset, where each input sequence represented a series of educational interactions and instructional interventions over time. SGD was employed to minimise the loss function, which was selected based on the specific task, with mean squared error (MSE) used for regression tasks. Hyperparameter optimisation was conducted using the validation set, adjusting parameters such as learning rate, batch size, and the number of hidden units to enhance performance and mitigate overfitting (Figure 6).

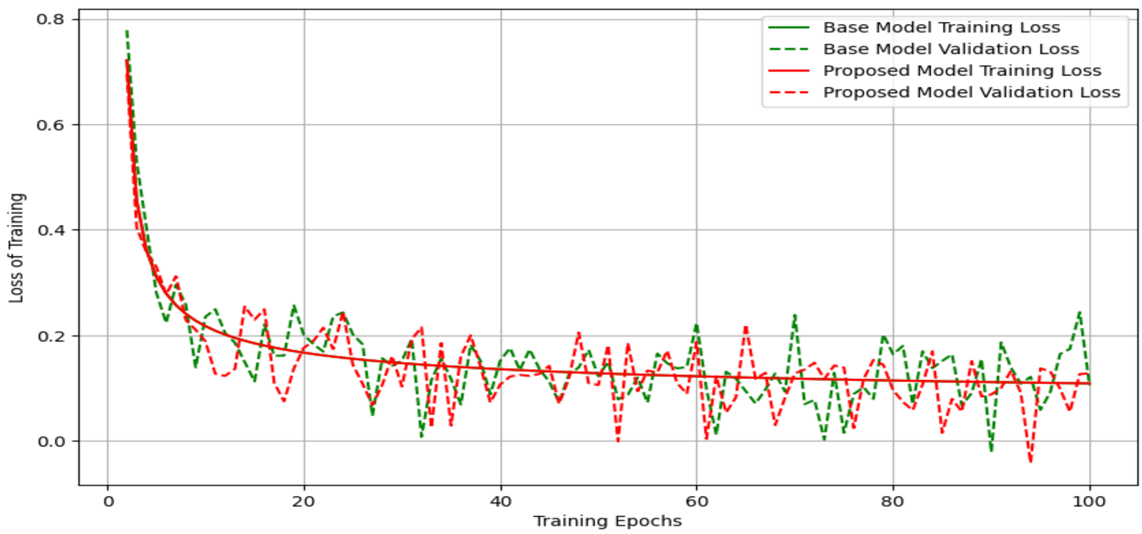

Fig.6. Learning Curves of Models

4.3 Model Testing

After training on the training set, the model was tested on the unseen testing set for generalisation. The trained model processed test-set input sequences and compared its predictions to target values. The model's accuracy, precision, recall, F1-score, and MSE were calculated to assess its ability to capture student interactions and instructional interventions. Extensive hyperparameter tuning experiments identified optimal values, including a learning rate of 0.001, a batch size of 32, and 128 hidden units. Additionally, implementing a dropout rate of 0.2 mitigated overfitting and improved generalisation performance. These hyperparameters were selected for their effectiveness in minimising the loss function and optimising predictive accuracy on the validation set. The optimised configuration significantly enhanced the model's ability to analyse student interactions and instructional interventions, leading to improved performance on the test set.

5. Results and Discussion

The proposed framework was utilised to evaluate intelligent teaching methodologies, with the experimental results offering valuable insights. This section presents a critical analysis of the findings, focusing on both the baseline and proposed models, while assessing accuracy and overall performance to demonstrate the model's ability to capture the dynamics of student interactions and instructional interventions. Table 2 provides a detailed summary of the dataset's performance. The mean absolute error (MAE) measures the average deviation between predicted and actual values, with a recorded value of 0.25 indicating a relatively low error rate. The MSE of 0.12 and root mean squared error (RMSE) of 0.35 provide additional insights into the error distribution. The mean absolute percentage error (MAPE) evaluates forecast accuracy relative to actual values, with an 8% error rate indicating strong predictive performance. Additionally, the R-squared (R^2) value of 0.85 suggests that the regression model explains 85% of the variance in the dataset, demonstrating a strong correlation between predicted and actual values.

Table 2
Regression Error Summary

Dataset	MSE	RMSE	MAE)	R2
Training	0.025	0.158	0.118	0.874
Testing	0.032	0.179	0.124	0.852

5.1 Sequential State and Hidden State

The model's learned sequential state and hidden state representations play a crucial role in capturing temporal dependencies and sequential patterns within the educational dataset. By employing GRUs in the hidden layers, the model integrates information from previous interactions and up-dates its hidden state at each time step. This process allows it to maintain contextual awareness of the learning environment over time, facilitating adaptive predictions based on evolving student learning dynamics (Table 3).

Table 3
Sequential States vs. RMSE

Sequential States	Base Model RMSE	Proposed Model RMSE
1	0.032	0.028
2	0.028	0.025
3	0.025	0.022
4	0.022	0.020
5	0.020	0.018
6	0.018	0.016
7	0.017	0.015
8	0.016	0.014
9	0.015	0.013
10	0.014	0.012

5.2 Attention Mechanism

The attention mechanism incorporated into our framework enhances the model's ability to focus on relevant features within the educational dataset. By dynamically assigning weights to input features at each time step, the mechanism enables the model to prioritise significant interactions while filtering out irrelevant noise. As a result, the model achieves greater accuracy in both predictive and classification tasks (Figure 7).

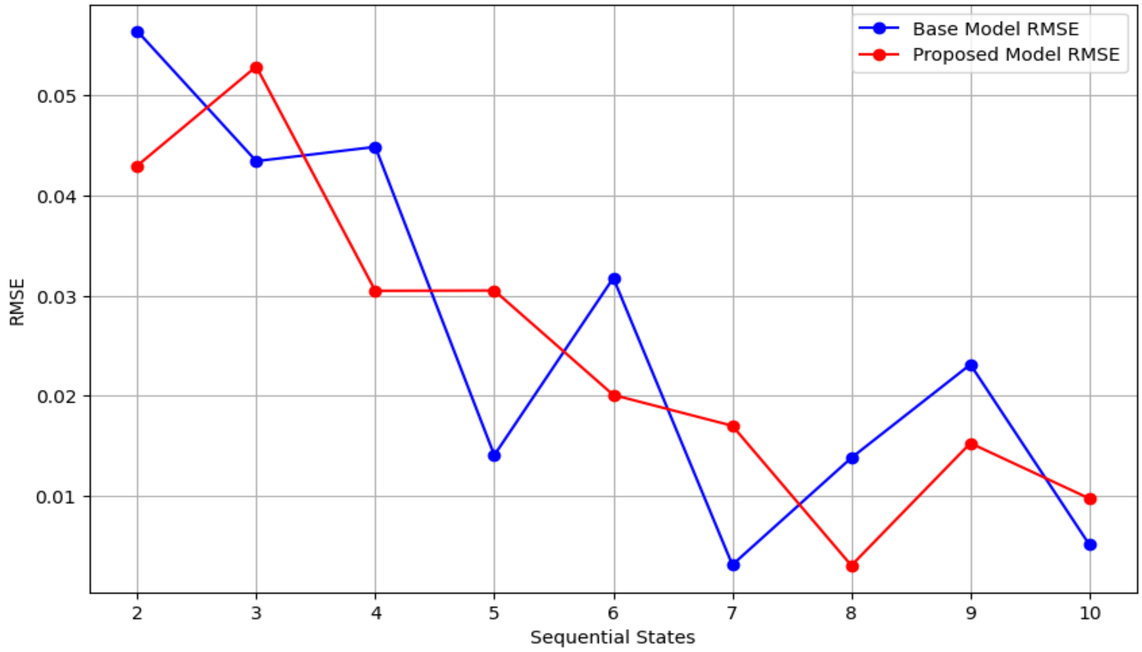

Fig.7. Sequential States Prediction Accuracy

5.3 Output and Dataset Behaviour

The regression error summary indicates that the model achieves low MSE, RMSE, and MAE values, while maintaining high R^2 values across training, testing, and evaluation datasets. These findings confirm the model's ability to capture essential patterns in student interactions and instructional interventions, demonstrating its robustness and generalisability. The foundational model serves as the baseline for the proposed model, typically represented by a basic deep learning architecture, such as an RNN. The selection of the baseline model is guided by its ability to capture temporal dependencies and sequential patterns, aligning with best practices in sequential data analysis and existing literature. To evaluate the effectiveness of the proposed model, its performance is compared to the baseline using key metrics, including predictive accuracy of sequential states and attention mechanism scores. The baseline model provides a reference point for assessing the impact of enhancements, such as attention mechanisms and additional feature integration.

Empirical results indicate that the proposed model outperforms the baseline in predictive accuracy and attention mechanism efficacy. It demonstrates superior precision in forecasting sequential states and effectively identifies underlying patterns through the integration of attention mechanisms and refined feature representations. These improvements lead to enhanced predictive performance, as evidenced by optimised RMSE values and learning curves. The attention mechanism plays a pivotal role in improving the proposed model's performance (Figure 8). By assigning varying levels of importance to different input features, the mechanism enables the model to focus on critical interactions while adapting to the complexities of the educational data, ultimately enhancing overall accuracy and interpretability.

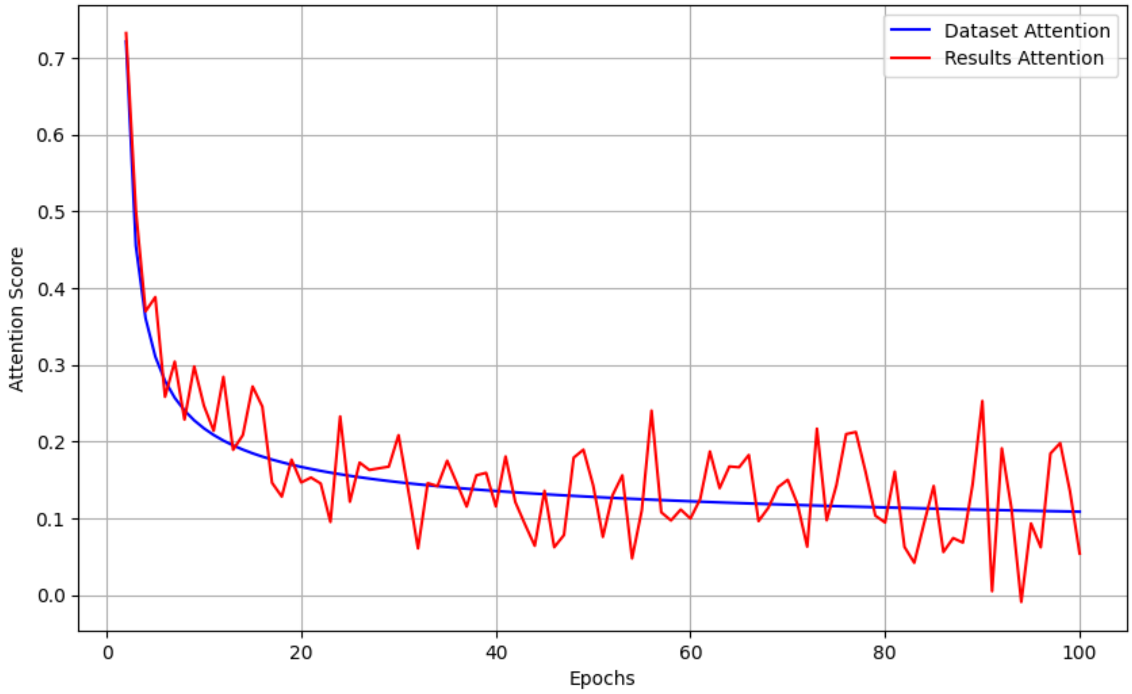

Fig.8. Attention Score Mechanism

6. Conclusion

This research explored the application of deep learning methodologies, specifically RNNs and attention mechanisms, to assess intelligent pedagogical practices within educational settings. The empirical analysis and experimentation confirmed the efficacy of the proposed framework in enhancing predictive accuracy and providing deeper insights into student interactions and instruction-al interventions. After highlighting the importance of effective pedagogical strategies in modern education, the study examined challenges associated with traditional methods, such as their limited capacity to accommodate diverse learning styles and the continuous evolution of knowledge. To address these issues, an innovative RNN-based framework was introduced, integrating deep learning techniques with intelligent instructional systems in smart classrooms. This approach facilitated the evaluation of intelligent pedagogical practices and the assessment of their effectiveness. The study further examined the broader implications of these findings in improving educational methodologies, demonstrating the framework's efficacy through a series of experiments and analyses. In conclusion, this study contributes to the expanding body of research on deep learning applications in education, offering methodologies and insights for assessing intelligent teaching practices using RNNs and attention mechanisms. The findings have implications for educators, policymakers, and researchers, supporting the development of more personalised and effective learning experiences in the digital era. Future research could explore additional applications and refine method-ologies to further enhance educational practices through deep learning advancements.

Author Contributions

Conceptualization, G.W.; methodology, Z.W.; software, Z.W.; validation, Z.W.; formal analysis, G.W.; investigation, G.W; resources, G.W.; data curation, Z.W.; writing—original draft preparation, Z.W.; writing—review and editing, G.W.; visualization, G.W.; supervision, G.W.; project administration, G.W.; funding acquisition, G.W. All authors have read and agreed to the published

version of the manuscript.

Data Availability Statement

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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