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AI-Based Adaptive Pedagogy: Optimization of Learning Pace for Improved Knowledge Retention and Student Motivation

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Abstract

Adaptive pedagogy driven by artificial intelligence (AI) has emerged as a promising paradigm to personalize learning pace and improve outcomes. Traditional methods provide limited insight into long-term knowledge retention, while existing reinforcement learning (RL) approaches often struggle with stability, convergence, and integrating motivational factors. These constraints reduce effectiveness in optimizing pace and sustaining learner engagement. The objective is to optimize instructional pace for improved knowledge retention and sustained motivation using a hybridized intelligent framework. An Enriched Proximal Policy mutated Recurrent Neural–Long Short-Term Memory Network (EPP-RN-LSTM Net) is introduced, combining sequential knowledge representation with a stable RL policy enhanced through evolutionary mutation and auxiliary predictors. The framework utilizes a Recurrent Neural Network (RNN) to model temporal dependencies, Long Short-Term Memory (LSTM) to capture the learner's state, an Enriched Proximal Policy (EPP)-based policy to determine adaptive instructional actions, and mutation strategies to enhance exploration. Pedagogy learning data involving performance scores, engagement indicators, derived metrics, learner profiles, interaction logs, and labels for motivation and retention were collected. Data preprocessing using z-score normalization ensures standardized scaling of features. Singular Value Decomposition (SVD) reduces redundancy and highlights dominant behavioral patterns. The experimental results outperform baseline models, with F1-score achieves 0.92, precision of 0.94, and recall of 0.90 indicating reliable retention prediction, adaptive learning, and effective motivation optimization. EPP-RN-LSTM Net provides an advanced adaptive pedagogy mechanism capable of aligning learning pace with individual needs while simultaneously enhancing retention and motivation.

Keywords: *Adaptive pedagogy, knowledge retention, learner motivation, Enriched Proximal Policy mutated Recurrent Neural – Long Short-Term Memory Network (EPP-RN-LSTM Net), educational.*

1. Introduction

Since the 21st century, learning approaches have changed due to societal shifts and technology breakthroughs, with a focus on individualized education, holistic individual development, and flexible approaches that incorporate learning networks, educational psychology, and cognitive science [1]. Flexible digital platforms, such as online, mobile, and Information and Communication Technology (ICT)-based tools, allow learners to advance at their own paces, improving retention of knowledge, fostering ongoing skill development, and guaranteeing easily available, customized training in a range of professional situations [2].

Traditional teaching approaches have drawbacks, such as poor collaborative learning, unequal participation, low social engagement, and decreased motivation. These issues delay overall academic and classroom performance, especially for children with learning difficulties [3]. Artificial Intelligence (AI) aids Digital Transformation of Education (DTE) by enabling personalized learning, strengthening teacher-student engagement, streamlining administration, increasing evaluation accuracy, and supporting efficient, data-driven educational management and governance [4]. Personalized learning encourages active involvement, metacognitive awareness, and better academic results by tailoring the speed, content, and teaching strategies to each student's unique requirements, interests, and qualities [5].

Research Objective

Conventional adaptive learning systems employ static pacing, which limits personalization, retention, and motivation. The research aims to optimize instructional pace for improved retention and sustained engagement. An intelligent framework overcomes these challenges by gathering multimodal student data, applying Z-score normalization, and extracting essential characteristics using Singular Value Decomposition (SVD). The proposed Enriched Proximal Policy mutated Recurrent Neural–Long Short-Term Memory Network (EPP-RN-LSTM Net) combines RNNs, LSTMs, and EPP to enable adaptive instructional activities that improve information retention, reduce dropout, and promote individualized learning. The key contributions include:

- To design an intelligent learning pace optimization model integrating RNNs, LSTMs, and EPP for adaptive instructional actions.
- To collect and preprocess pedagogy learning data using Z-score normalization and extract features via SVD for improved behavioral and performance representation.
- To evaluate the EPP-RN-LSTM Net, demonstrating higher accuracy, stronger recall, balanced precision and improved learner motivation.

The remaining sections are organized as follows: Section 1 introduces adaptive pedagogy challenges, followed by a review of related studies in Section 2, the EPP-RN-LSTM Net methodology is explained in Section 3, results and discussion are presented in Section 4, and conclusions with future directions are discussed in Section 5.

2. Related works

For online learning, an entropy-enhanced Proximal Policy Optimization (PPO) algorithm and Attentive Knowledge Tracing (AKT) were employed to develop an adaptive learning path navigation (ALPN) system [6]. Despite the computational challenges, the results demonstrated better learning outcomes and more diverse, individualized learning paths. A generative AI-based personalized adaptive learning (PAL) system with a diffusion model was presented to improve deep knowledge tracing (DKT) [7]. Despite issues with data scarcity, the results showed better prediction accuracy and more useful recommendations for personalized learning. Engineering classes used an adaptive learning technique that included micro-learning, flipped classrooms, and self-regulated learning [8]. Despite the methodological complexity, the results demonstrated better student learning, engagement, and the development of disciplinary and transversal competencies.

An Attention-aware convolutional Stacked bidirectional long Short-Term memory (BiLSTM) network (ASIST) designed to predict student performance [9]. The results showed better representation learning, precise categorization, and improved early identification of at-risk learners with the variable performance of the datasets. An Actor-Critic framework-enhanced Deep Neural Network (EDNN) was suggested for optimizing individualized learning paths [10]. The results showed enhanced accuracy, more adaptability, and faster convergence in learning path suggestions despite integration constraints.

Despite advancements in AI-driven adaptive learning, certain challenges remain. Entropy-enhanced PPO with AKT improves learning path variation while posing computational hurdles [6]. Diffusion model-based PAL improves knowledge traceability but suffers from data scarcity [7]. Micro-learning, flipped classrooms, and self-regulated techniques increase engagement but it methodologically challenging [8]. ASIST accurately predicts performance but is sensitive to the dataset [9], whereas Actor-Critic EDNN improves flexibility but has integration restrictions [10]. Current methods prioritize accuracy but frequently lack long-term memory, motivation, and real-time flexibility, emphasizing the importance of a unified, strong adaptive learning framework. To address such limitations, An EPP-RNN-LSTM Net was created by merging LSTM, RNN, and EPP to improve retention prediction, optimize learning pace, and increase motivation, resulting in a scalable AI-driven solution for personalized education.

3. Methodology

A hybrid AI framework simulates student behavior to maximize instructional pace. Pedagogy learning data are preprocessed with Z-score normalization, and essential features are retrieved using SVD. The EPP-RN-LSTM Net combines RNNs for short-term engagement, LSTMs for long-term retention, and EPP for adaptive behaviors, hence improving retention, motivation, and individualized learning results. The proposed method's overall procedure is depicted in Figure 1.

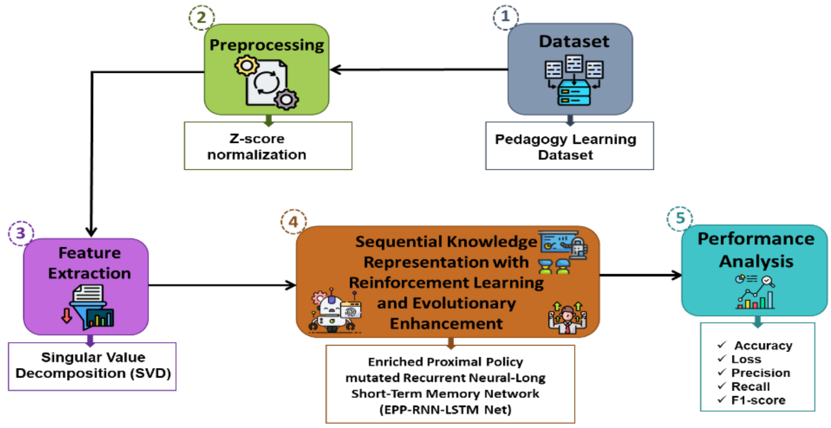

Figure 1: Methodology flow

3.1 Data collection

The learner data were accessed through pedagogy learning data available on Kaggle (https://www.kaggle.com/datasets/ziya07/multimodal-student-retention-dataset). The dataset includes 1,800 records and 24 attributes that capture learner profiles, interaction logs, performance scores, engagement indicators, derived metrics, and target labels for retention and motivation. Its complete structure enables Deep Learning (DL)-based modeling of educational behaviors, adaptive teaching tactics, retention prediction, and motivational optimization across a wide range of learning scenarios.

3.2 Data Preprocessing using Z-score normalization

Z-score normalization generates a single scale from feature data, ensuring that academic measures, demographic attributes, attendance habits, and advising notes contribute similarly throughout model training. Each feature is changed by removing its mean and dividing by its standard deviation, represented in Equation (1).

$$Z_j' = \frac{F_j - \bar{F}}{S_F} \tag{1}$$

Where, S_F denotes standard deviation, F_j denotes the actual feature value, $\bar{F}$ refers to the mean of all features across learners, and Z_j' indicates the standardized value. Z-score normalization creates a consistent dataset that improves convergence, retention prediction, and individualized learning speed optimization by standardizing all features, eliminating scale biases, and highlighting relative differences in engagement and performance.

3.3 Singular Value Decomposition (SVD) for Feature Extraction

SVD reduces dimensionality for effective model training while identifying dominating patterns in academic indicators, engagement features, and learner interaction logs. Any real matrix M can be decomposed in Equation (2).

$$M = U\,\Sigma\,\mathrm{V}^{\mathrm{T}} \tag{2}$$

Where T denotes the input data matrix, while the orthogonal matrices U and V represent the left and right singular vectors, respectively. SVD maintains invariance to scaling or rotation, stabilizes against noise, and preserves important components. By projecting high-dimensional learner and engagement data into a smaller singular-value space, important behavioral and performance cues are preserved, which enables the EPP-RN-LSTM Net to better predict motivation and retention, optimize instructional pacing, and capture temporal dependencies.

3.4 Enriched Proximal Policy mutated Recurrent Neural–Long Short-Term Memory Network (EPP-RN-LSTM Net)

The EPP-RN-LSTM Net captures motivation and performance cues to improve retention and personalize learning, combining mutation-based EPP for adaptive pacing, LSTMs for long-term retention, and RNNs for short-term engagement.

Recurrent Neural-Long Short-Term Memory Network (RN-LSTM Net)

The RN-LSTM Net combines RNN for sequential learner progress with LSTM Net for long-term engagement signals, allowing for adaptive pace, accurate retention prediction, and tailored knowledge maximization.

RNN: RNNs handle sequential learning data, where every decision about pacing depends on previous learner interactions. In adaptive pedagogy, RNNs track logs like quiz performance, engagement levels, and response intervals to generate a temporal state based on progression trends. The recurrent update is modelled as Equations (3-4).

$$s_k = \phi(A_d v_k + B_d s_{k-1} + b_d) \tag{3}$$

$$y_k = \phi(C_d s_k + d_d) \tag{4}$$

where y_k denotes the learner input at step k, s_k is the hidden state, s_{k-1} represents memory from the previous step, A_d, B_d, and C_d are trainable matrices, d_d, b_d are biases, and ϕ signifies a nonlinear activation. RNNs provide representations that combine current learning activity with past engagement trends by updating hidden states across sequences, tracing progression patterns, identifying knowledge gaps, and generating adaptive pacing signals.

LSTM Net: LSTM Net improves RNNs by incorporating gates that control information retention, forgetting, and updating, hence resolving gradient instability and enabling long-range learning dependencies. In adaptive pedagogy, LSTMs control how immediate engagement and historical performance are integrated for pacing optimization. The transition process is defined in the following Equations (5-6).

$$p_k = \sigma\left(A_p v_k + C_p s_{k-1} + b_p\right),\ q_k = \sigma\left(A_q v_k + C_q s_{k-1} + b_q\right),\ r_k = \sigma(A_r v_k + C_r s_{k-1} + b_r) \tag{5}$$

$$\widetilde{m}_k = \tanh(A_m v_k + C_m s_{k-1} + b_m),\ m_k = q_k \odot m_{k-1} + p_k \odot \widetilde{m}_k,\ s_k = r_k \odot \tanh(m_k) \tag{6}$$

where p_k, q_k, r_k represent input, forget, and output gates with corresponding biases (b_p, b_q, b_r,b_m), $\widetilde{m}_k$ denotes the candidate memory, m_k refers to the updated memory cell, m_{k-1}denotes previous hidden state, s_k indicates the hidden state, and $\odot$ denotes element-wise multiplication. The input and recurrent weights of matrix A and C constitutes (A_p, A_q, A_r, A_m) and (C_p, C_q, C_r, C_m). The sigmoid and hyperbolic tangent function is indicated by $\sigma$and tanh. LSTMs create stable temporal representations that direct instructional pacing, enhance learning continuity, and sustain motivational alignment across educational engagements by maintaining a balance between long-term retention signals and short-term engagement dynamics through gated memory updates.

Enriched Proximal Policy (EPP) optimization

PPO maintains instructional pacing by modifying teaching tactics using reinforcement learning; however, it is frequently constrained by unstable training, slow convergence, and inadequate sensitivity to motivation cues. EPP solves these difficulties by merging mutation-based exploration with retention and engagement factors. The PPO employs a clipped surrogate loss that is derived in Equations (7).

$$J^{PPO}(\psi) = \mathbb{E}_k[\min(\rho_k(\psi)B_k, clip(\rho_k(\psi), 1-\delta, 1+\delta)B_k)] \tag{7}$$

Where $J^{PPO}(\psi)$ denotes the standard policy objective, $\rho_k(\psi) = \frac{\pi_\psi\,(u_k|z_k)}{\pi_{\psi^-}(u_k|z_k)}$, u_k denotes adaptive pacing action, z_k indicates learner state representation, and π_ψ refers to policy with parameters ψ, B_k as the advantage, and δ as the clipping bound. EPP extends this by introducing mutation strategies and motivational predictors, which are expressed in Equation (8).

$$J_{actor}^{EPP}(\psi) = J^{PPO}(\psi) + \alpha Q_k, \quad J_{critic}^{EPP}(\eta) = \mathbb{E}_k\left[\left(Y_k - V_\eta(z_k, H_k)\right)^2\right] \tag{8}$$

Where $J_{actor}^{EPP}(\psi)$ denotes enriched actor objective with adaptive exploration and auxiliary cues, Q_k represents auxiliary motivation–retention cues, α is a balancing coefficient, Y_k indicates the return, and V_η denotes the value function with parameters η enriched by cues H_k. By improving exploration, stabilizing updates, and ensure that pacing choices take motivation and learning performance into account, the enriched design improves retention and lowers dropout rates.

The EPP-RN-LSTM Net employs LSTM for temporal encoding, RNN for sequential modeling, and EPP for adaptive decisions, resulting in exact retention prediction, dynamic learning pace adjustment, and increased learner motivation across a variety of learning behaviors.

4. Results and Discussion

The EPP-RN-LSTM Net was implemented using Python 3.11 on a workstation with an Intel Core i9, 64GB RAM, and NVIDIA RTX 4090 GPU, enabling quick model training, simulation, and evaluation using multimodal student retention data.

Accuracy is described as the fraction of accurately predicted learner outcomes among all predictions, indicating how accurately the model matches actual results and providing an overall measure of predictor performance. Loss quantifies the difference between expected and actual outcomes, which helps guide training optimization to reduce errors and increase prediction quality. Precision refers to the fraction of accurately identified positive outcomes, demonstrating reliability in detecting at-risk learners and assuring trustworthy predictions. Recall quantifies the fraction of true positive cases captured, monitoring sensitivity to engagement or dropout events, and enabling prompt responses. The F1-score integrates precision and recall into a single statistic, combining reliability and sensitivity, allowing for a more comprehensive evaluation of model effectiveness and improved information retention and motivation.

The visualizations show EPP-RN-LSTM Net performance throughout 30 epochs. Accuracy progressively increases, with training at 0.98 and validation at 0.96, while loss gradually reduces. This simultaneous increase suggests consistent training, successful convergence, and a high predictive ability for adaptive learning, retention forecasting, and learner engagement optimization. The accuracy and loss progression during training and validation are displayed in Figure 2 (a-b).

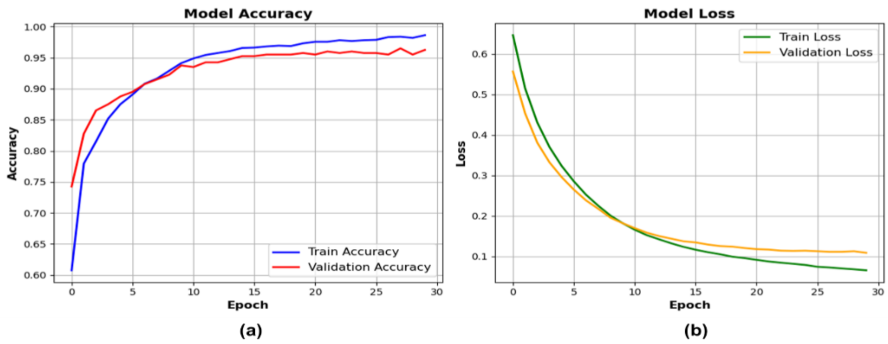

Figure 2: Training and validation (a) accuracy and (b) loss.

The comparison of the proposed EPP-RN-LSTM Net is evaluated using Precision, Recall, and F1-score against Pre-trained Neural Network (NN) [11], Artificial Neural Network (ANN) [11], K-Nearest Neighbor (KNN) [11], Support Vector Machines (SVM) [11], Gradient Boosting [11], and Random Forest (RF) [11]. Table 1 and Figure 3 compare EPP-RN-LSTM Net with baseline models, showing F1-score 0.92, precision 0.94, and recall 0.90, highlighting superior predictive accuracy, retention forecasting, and engagement optimization.

Table 1: Model effectiveness measured by key metrics

Methods	Precision	Recall	F1-score
Pre-trained NN [11]	0.88	0.74	0.80
ANN [11]	0.81	0.79	0.80
SVM [11]	0.84	0.85	0.84
Gradient Boosting [11]	0.76	0.87	0.81
RF [11]	0.82	0.80	0.81
KNN [11]	0.88	0.74	0.80
EPP-RN-LSTM Net [Proposed]	0.94	0.90	0.92

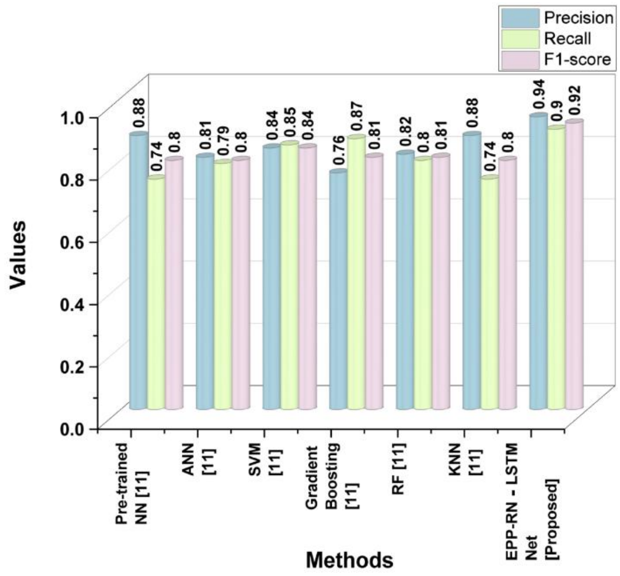

Figure 3: Comparison of model effectiveness.

An AI-based adaptive pedagogy system based on EPP-RN-LSTM Net was created to optimize learning pace, improve knowledge retention, and maintain students motivation. Existing models frequently had issues with unstable convergence, poor temporal learning pattern modeling, and a lack of integration of engagement or retention cues. Pre-trained NN [11] and ANN [11] demonstrated moderate prediction performance but could not capture sequential learner behaviours. Although SVM [11] and Gradient Boosting [11] failed to dynamically adapt instruction and were susceptible to feature scale, the models offered respectable classification accuracy. RF [11] and KNN [11] performed well on static data but struggled to simulate time-dependent performance patterns. To overcome the issues, an EPP-RN-LSTM Net is established that incorporates sequential state encoding, policy-guided adaptive decisions, and mutation-driven exploration, with retention and engagement signals refining predictions, resulting in a robust, flexible, and accurate learning pace and motivation.

5. Conclusion

An adaptive AI-driven mechanism was developed to optimize learning pace, knowledge retention, and learner motivation. Learning data from pedagogy, such as learner profiles, interaction logs, performance ratings, engagement metrics, derived metrics, and labels for motivation and retention, were collected and standardized using z-score normalization. Key behavioral and performance features were extracted through SVD to capture essential temporal patterns. The proposed EPP-RN-LSTM Net integrates RNNs for short-term engagement, LSTMs for long-term retention, and EPP with evolutionary mutation for adaptive instructional actions. The experimental findings outperformed the baseline models, with a training accuracy of 0.98, validation of 0.96, F1-score of 0.92, precision of 0.94, and recall of 0.90, indicating reliable retention prediction, adaptive learning, and effective motivation optimization. Limitations included dependency on dataset size, diversity, and potential computational overhead for real-time deployment. Future research will explore integration with larger and more diverse student datasets, multimodal feedback incorporation, and reinforcement learning variants for improved adaptability and scalability.

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